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In re **Distribution of Satellite Royalty Funds**	**DOCKET NUMBER 14-CRB-0011-SD (2010-13)**

ALLOCATION PHASE REBUTTAL CASE OF THE COMMERCIAL TELEVISION CLAIMANTS

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The Broadcaster Claimants Group ("BCG"), on behalf of the Commercial Television Claimants ("CTV"), hereby submits its rebuttal case evidence in the Allocation Phase of the 2010-2013 Satellite Copyright Royalty Distribution Proceeding.

I. CTV'S REBUTTAL CASE EVIDENCE

CTV's rebuttal case evidence consists of the testimony of the following witnesses, along with associated exhibits:

1. **Dr. Christopher Bennett**, Principal, Bates White Economic Consulting.

Dr. Bennett provides rebuttal testimony regarding Dr. Gray's Amended Written Direct Testimony and additional data analyses regarding the Testimony of Dr. William J. Brown and Amended Testimony of John S. Sanders.

2. **Dr. Randal Heeb**, Partner, Bates White Economic Consulting.

Dr. Heeb presents rebuttal testimony to the Amended Written Direct Statements of Dr. Erkan Erdem and Professor Daniel L. Rubinfeld.

Respectfully submitted,

COMMERCIAL TELEVISION CLAIMANTS

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Its Counsel

Dated: August 26, 2019

Before the
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WASHINGTON, D.C.

In the Matter of	)	
	)	**CONSOLIDATED PROCEEDING**
Distribution of Satellite Royalty Funds	)	**No. 14-CRB-0011-SD (2010-13)**

REBUTTAL TESTIMONY OF CHRISTOPHER J. BENNETT, PhD

August 26, 2019

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I. Background

(1) I am a Principal at Bates White, LLC, an economic consulting firm based in Washington, DC. My educational background, experience, and credentials were presented as part of my written direct testimony submitted in this proceeding on March 22, 2019.

(2) Staff at Bates White under my supervision assisted me with the preparation of this rebuttal analysis and report.

II. Overview and scope of testimony

(3) I was asked by counsel for the Commercial Television Claimants (CTV) to review and analyze the viewing-related study presented in the Testimony of Jeffrey S. Gray, PhD, submitted in this proceeding on March 22, 2019 ("Gray Report") and the Amended Testimony of Jeffrey S. Gray, PhD, submitted in this proceeding on June 7, 2019 ("Amended Gray Report").

(4) As part of this analysis, I reviewed the Gray Report and Amended Gray Report together with Dr. Gray's reliance materials, which include the Direct Testimony of Paul Lindstrom. I also reviewed transcripts and reports from prior proceedings.

(5) After reviewing these materials and conducting my own analysis, I have formed the following opinions:

- Dr. Gray's viewership study is flawed and unreliable because, among other things:
  - The underlying raw Nielsen data are deficient because they are sparse and untethered to the population of households that actually received signals on a distant basis
  - Dr. Gray provided no evidence that his "enhanced" viewing analysis corrected any of the deficiencies in the underlying raw Nielsen data
  - Dr. Gray applied separate regressions for WGNA and the non-WGNA stations, thereby underweighting WGNA's influence in his ultimate viewing share calculations
  - Dr. Gray's confidence intervals are incorrectly calculated and do not account for the uncertainty in the underlying raw Nielsen data
  - Dr. Gray's total viewing regression is unreliable and yields nonsensical viewing predictions
- These fundamental issues with Dr. Gray's data and with his viewership study, together with other conceptual and methodological issues discussed below, render Dr. Gray's reported royalty shares unreliable.
- Even if relative program viewership actually did provide "a reasonable and reliable measure of the relative economic value of distantly retransmitted programming,"[1] Dr. Gray has not reliably measured relative program viewership.

(6) An explanation of each of these opinions follows below.

(7) I was also asked by counsel for the CTV to provide certain additional data analyses regarding the Testimony of Dr. William J. Brown ("Brown Report") and the Amended Testimony of John S. Sanders

[1] *See* Amended Testimony of Jeffrey S. Gray, June 7, 2019 [hereinafter "Amended Gray Report"], ¶ 102.

("Sanders Report"), submitted in this proceeding on March 22, 2019 and June 7, 2019, respectively. The results of my analyses are presented below.

III. Overview of Dr. Gray's report

(8) As I understand it, Dr. Gray undertook to measure the relative amount of viewing by satellite households of different categories of programs that aired on retransmitted distant stations.[2] I further understand that Dr. Gray provided lists of those retransmitted distant stations to Gracenote, Inc. ("Gracenote").[3] Dr. Gray also provided those same lists to Mr. Lindstrom, along with a list prepared by the Cable Data Corporation (CDC) showing the counties in which each of the stations was to be considered "local" (i.e., not a distant signal).[4] Gracenote then provided Dr. Gray with information in its database, if any, about programs that aired on the distantly retransmitted stations; and Mr. Lindstrom provided Dr. Gray with information in the Nielsen database, if any, about satellite household viewing of programming on the distantly retransmitted stations by quarter hour, with viewing by satellite households separated between distant and local viewing.[5]

(9) I understand from their testimony and supporting materials that all of the viewing data provided by Mr. Lindstrom to Dr. Gray were collected in satellite households included in Nielsen's National People Meter Sample[6] and that Dr. Gray used weighted household viewing counts rather than the weighted household minutes of viewing data that were also provided by Mr. Lindstrom.

(10) I further understand that Dr. Gray did not directly include the raw Nielsen distant viewing data provided to him by Mr. Lindstrom when he calculated the volume and share of viewing by claimant category. Instead, he developed regression-based models purportedly correcting for deficiencies in the raw Nielsen distant viewing data.[7] Then, in his ultimate ("preferred") viewing share analyses, Dr. Gray relied on distant household counts projected from his regression models, supplanting all of the actual distant household counts in the raw Nielsen viewing data.

2 Amended Gray Report, ¶ 102.

3 Amended Gray Report, ¶ 47.

4 Direct Testimony of Paul B. Lindstrom, Mar. 22, 2019 [hereinafter "Lindstrom Report"] at 4.

5 Lindstrom Report at 4 and 5; Amended Gray Report, ¶ 44.

6 In his supporting materials, Mr. Lindstrom states that "[t]he current MPAA Local/Distant Viewing exposure is based on Stated Coded viewing in the National People Meter Sample" (PS-001792 - PS-001794 at 1).

7 Amended Gray Report, ¶¶ 37, 62, 63.

IV. Overview of Nielsen data

(11) Nielsen provided Dr. Gray with Household Meter Data.[8] Dr. Gray acknowledges that these data represent estimates that were derived from a sample, and he refers to them as "Nielsen's raw *estimated* viewing data."[9] According to Dr. Gray, "Nielsen performed custom analyses to estimate the level of viewing by satellite-subscribing households to all television stations, respectively, for each fifteen-minute interval (quarter hour) of the day, each day for 2010 through 2013. From its estimates of total metered viewing, Nielsen extracts both the local and distant viewing to stations retransmitted by satellite carriers for 2010 through 2013."[10]

(12) Nielsen actually provided Dr. Gray with several data fields relevant to distant viewing. Specifically, for each recorded instance of distant viewing, these fields included:

1. The number of sampled households for which viewing was recorded (Household_Count)
2. The aggregate number of households that are represented by the Nielsen sampled viewing households (Sum_of_Daily_Household_Weight)
3. Total minutes of viewing by the sampled viewing households (Total_Minutes)
4. The aggregate number of minutes of viewing that are represented by the total minutes of viewing by the Nielsen sampled viewing households (Total_Minutes_WGT)

(13) Collectively, these data contain information about the number of sampled households viewing a program and the duration of that viewing. Despite having access to viewing minutes data and asserting that the duration of viewing as measured by minutes is relevant to a viewing study,[11] Dr. Gray nevertheless failed to consider any of this information as part of his viewing study. Indeed, Dr. Gray dropped all of the viewing fields that Nielsen provided to him except for the Sum_of_Daily_Household_Weight variable (hereafter "Distant viewership (Nielsen)").

(14) Figure 1 shows that that the actual *volume* of viewing by a household as measured in minutes varies substantially in the raw Nielsen data. For example, the raw Nielsen data record a single household watching Sports Zone for a full quarter hour on January 10, 2010, and a single household watching Sports Zone for only 1/15 of a quarter hour on January 4, 2010. Yet, because Dr. Gray ignored the minute variables, he assigned equal weight to the two pairs of programs listed in Figure 1 and hence treated them identically even though the duration of viewing is clearly different.

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8 Amended Gray Report, ¶¶ 43, 62.

9 Amended Gray Report, ¶ 42 (emphasis added).

10 Amended Gray Report, ¶ 44.

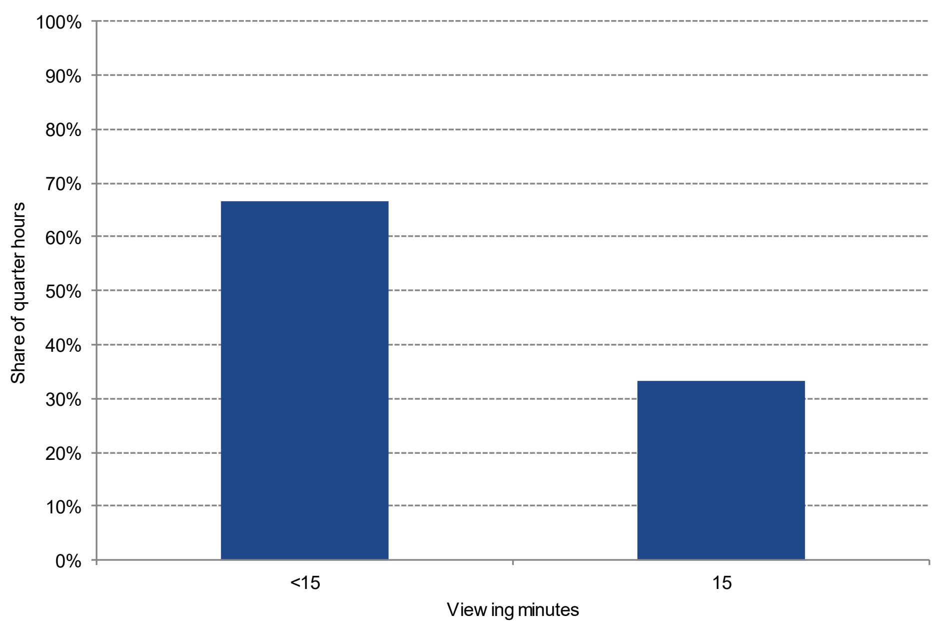
11 "Therefore, a measure of the happiness, or "utility," an individual subscriber gets from a specific program is the number of minutes that subscriber spends viewing the program offered to him or her by the satellite system." Amended Gray Report, ¶ 21.

Figure 1: Examples of different viewing times for consecutive quarter hours

Call sign	Start time	Title	Total minutes	Sum of daily household weight	Total minutes weighted
KABCDT	1/10/2010 17:45	Sports Zone	15	15,693	235,395
KABCDT	1/4/2010 18:00	Sports Zone	1	15,693	15,693
WJTVDT	1/7/2010 17:15	News Channel 12 at 5p	1	16,273	16,273
WJTVDT	12/1/2010 17:30	CBS Evening News With Katie Couric	15	16,273	244,095

(15) The examples in this table were not drawn from a small isolated set of viewings. According to the Nielsen data, it is actually quite common to observe households watching less than a full quarter-hour of programming. Figure 2 below, for example, shows that a significant portion of quarter hours in the Nielsen data are not viewed for a full quarter-hour, a point that is entirely ignored in Dr. Gray's analysis.[12]

Figure 2: Distribution of partial (<15 min) and full quarter-hour viewing records (Nielsen data)—2010



(16) Even if Dr. Gray had taken account of the viewing minute variables available from Nielsen, the overall data on viewing of distantly retransmitted programming are sparse. On an annual basis, for example, Nielsen provided Dr. Gray with recorded viewing instances for approximately only 7% of

[12] The 15-minute bucket in Figure 2 includes instances where the average distant viewing minutes per quarter hour are greater than 15. These account for approximately 3.3% of quarter hours.

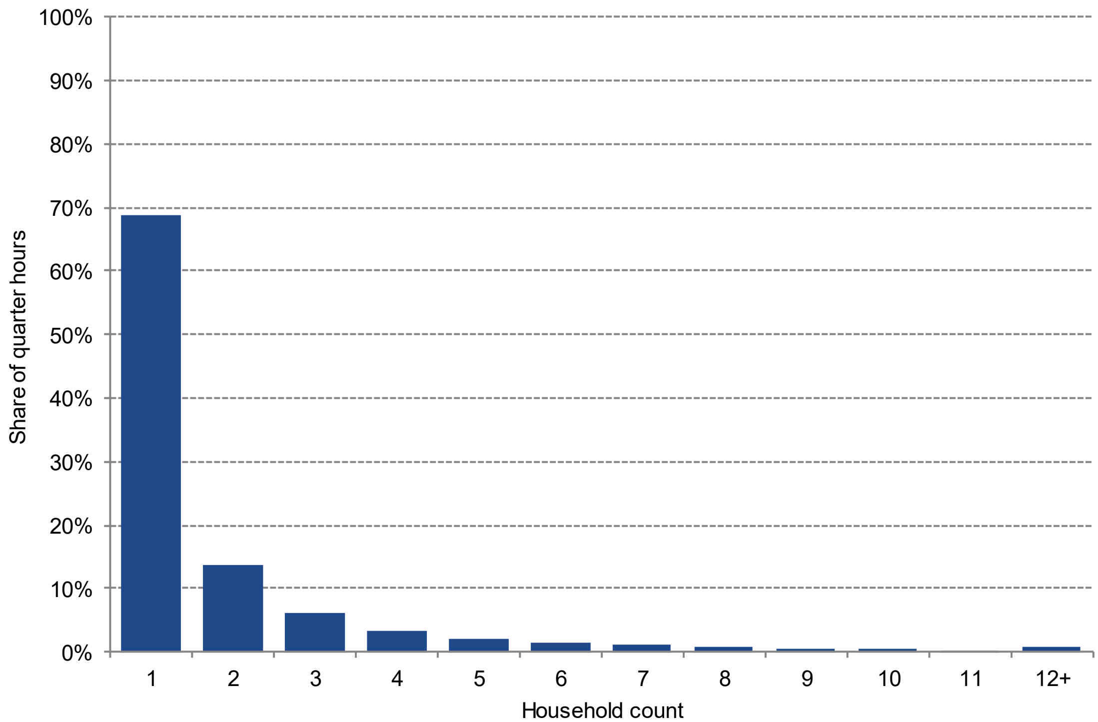
the relevant quarter hours. Thus, for 93% of quarter hours, Dr. Gray was provided with no data showing any distant viewing. Figure 3 below shows that for each year, between 92.8% and 94.1% of quarter hours in Dr. Gray's data contained no record of distant viewing.

Figure 3: Volume of programming with no viewership data

Year	Volume of programming (by quarter hours) in Dr. Gray's database	Percent with no distant viewing record
2010	2,759,526	92.8%
2011	3,042,639	94.1%
2012	3,067,238	93.5%
2013	2,717,685	93.3%

(17) Having viewing data for only 7% of the relevant quarter hours is a significant limitation. However, the Nielsen data are further limited by the fact that a majority of the available viewing records are based on viewing by a single household. Figure 4 below demonstrates this fact, showing that nearly 70% of the viewing records in the Nielsen sample reflect viewing by a single household.

Figure 4: Proportion of quarter hours by distant household count (Nielsen data)—2010



(18) The Nielsen data are clearly sparse, and Dr. Gray cites this sparsity as one of his principal reasons for undertaking his regression analysis.[13] The other principal reason is that Dr. Gray considers the household weights that he relied on to be detached from the actual populations of distant subscribers.[14] Indeed, according to Dr. Gray, the raw Nielsen data are not to be relied on because they "[ignore] the number of subscribers who have access to programming carried on distantly retransmitted signals."[15]

(19) Dr. Gray's concerns with the raw Nielsen household data and the sampling weights in particular are legitimate. The household weights provided by Nielsen often result in extrapolated household counts that exceed the total number of households receiving a signal on a distant basis (as determined from the CDC data). Figure 5 demonstrates this, with examples showing that Nielsen sometimes ascribes more than 10 times the actual number of distant subscribers as the number of viewing households in a given quarter hour.

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13 Amended Gray Report, ¶ 63.

14 Amended Gray Report, ¶ 64

15 Amended Gray Report, ¶ 69.

Figure 5: Programs with higher distant viewership than total distant subscribers

Call sign	Title	Date	Distant subscribers (CDC)	Distant viewership (Nielsen)
WCAU	The Voice	10/29/2012	24,702	249,351
WAPT	Good Morning America	9/28/2011	4,515	50,697
WCBS	The Bold and the Beautiful	12/14/2012	382,745	426,942
WMAQ	NFL Football	10/10/2010	1,924	32,718
WTTV	High school football	11/23/2012	9,373	39,063

(20) In summary, the Nielsen viewing data are sparse and the available positive household viewing data are unreliable. Most of the positive viewing household data reflect viewing by single households, and many of Nielsen's extrapolated household counts exceed the actual number of potential viewing households.

V. Dr. Gray's distant viewing analysis is flawed and unreliable

(21) Dr. Gray's measure of distant viewership for compensable programs carried by stations is flawed and unreliable. Moreover, the royalty shares Dr. Gray extrapolates based on his invalid viewing measure are invalid and unreliable.

V.A. Overview of Dr. Gray's "enhanced" viewing analysis

(22) As in the cable matter, Dr. Gray did not rely on the raw Nielsen viewing data for his viewing analysis. Instead, all his viewing share calculations were based on first imputing average viewing and then supplanting either most or all of the raw Nielsen viewing data with imputed data. In this section, I describe Dr. Gray's approach to imputing data, which includes separate regressions for WGNA and non-WGNA stations. I provide a mathematical explanation of Dr. Gray's regressions, as well as exhibits to explain how he arrives at his predictions of viewing, which he describes as "enhanced."

(23) Before proceeding, however, it is important to recall that the deficiencies in the raw Nielsen data result from Nielsen providing Dr. Gray with results from a *national survey* that samples small numbers of households, if any, from distant subscriber populations and includes sampling weights intended for estimating national viewing levels.[16] Thus, the viewing data are sparse and the sampling weights from the national survey are untethered to the actual number of distant household subscribers.[17]

(24) To purportedly correct for the deficiencies in the raw Nielsen data, Dr. Gray proposed three viewing models. Each of his models is based on a Poisson regression that relates a measure of distant viewing to (i) the number of distant subscribers, (ii) program type as defined in the Gracenote data, and (iii) the quarter hour in which the program aired. Specifically, Dr. Gray assumed that the correct levels of actual distant viewing can be well approximated by replacing the raw Nielsen data with *average* viewing based on the number of distant subscribers (S), quarter hour (q), and program type (p). The precise mathematical relationship for determining the within-group (i.e., the within subscriber, quarter-hour, and program-type) averages is computed using the following mathematical formula:[18]

$$\widehat{Viewing}(S, q, p) = \exp\left(\beta_C + \beta_S \ln(S) + \beta_q + \beta_p\right).$$

(25) The differences between Dr. Gray's three models lie in the data that he used to estimate the parameters β_C, β_S, β_q, and β_p that determine the values of the within-group averages, and whether he

[16] Amended Gray Report, footnote 25.

[17] Dr. Gray conceded this point, arguing that an approach based on the raw Nielsen weighted data "ignores the number of subscribers who have access to programming carried on distantly retransmitted signals." Gray Report, ¶ 69.

[18] The term *ln(S)* denotes the natural logarithm of the number of subscribers.

used his predicted average viewing to supplant all or only some of the raw Nielsen weighted viewing data.[19] Figure 6 below summarizes these differences.

Figure 6: Summary of Gray's "Enhanced" Viewing models[20]

Model	Input data	"Enhanced" viewing
Model 1[21]	Nielsen raw weighted viewing + zeros in place of missing quarter hours	Supplant all raw Nielsen viewing data, zeros, and missing values with predicted values
Model 2	Nielsen raw weighted viewing data only	Supplant all raw Nielsen viewing data, zeros, and missing values with predicted values
Model 3	Nielsen raw weighted viewing data + zeros in place of missing quarter hours	Supplant only zeros and missing values with predicted values

(26) In contrast to the approach that he adopted in the cable case, Dr. Gray performed separate regressions for WGNA and other non-WGNA stations distantly retransmitted on satellite systems. Dr. Gray allegedly performed these separate regressions for WGNA and non-WGNA stations for each model "because the signal WGNA is distinct in the number of subscribers reached on a distant basis."[22]

(27) In the cable case, Dr. Gray also included a measure of local viewing in his regression model, stating, "[I]t is possible to obtain reliable estimates of distant viewing for all retransmitted programs by also relying on Nielsen measures of household viewing in each retransmitted station's local market."[23] According to Dr. Gray:[24]

> The regressions [in the cable matter] demonstrate that there is a positive and statistically significant relationship between local viewing and distant viewing. The greater the number of people viewing a particular program on a per capita local basis, all else equal, the higher the level of distant viewing.

(28) Dr. Gray excluded his measure of local viewing in the satellite matter without providing any explanation.

(29) In the absence of a local viewing measure, Dr. Gray's non-WGNA regression assigns an average level of viewing to all programs airing on a given station within a given month that are of the same

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19 One each of the quarter hour and program types are subsumed in the constant, so there are 95 distinct values of the parameters β_q and 29 (14) distinct values of the parameters β_p in the non-WGNA (WGNA) regressions.

20 Dr. Gray applies each model to WGNA alone and then separately to the collection of all other non-WGNA stations. *See* Gray Report, footnote 26.

21 Contrary to Dr. Gray's assertion, this model was not presented in the past cable allocation proceeding. Indeed, Dr. Gray included an additional covariate in that regression model, namely what he called "local ratings." Second Corrected and Amended Testimony of Jeffrey S. Gray, Jan. 22, 2018 [hereinafter "Gray Cable Report"], Appendix C.

22 Gray Report, footnote 26.

23 Gray Cable Report, ¶ 35.

24 Gray Cable Report, ¶ 36.

program type—based on Gracenote's program-type classification—and airing within the same quarter hour. For example, Dr. Gray assigned all "news" programs airing in 2010 in quarter hour 60 on WABC the exact same level of viewing, and all "playoff sports" programs airing in 2012 in quarter 72 on WCBS the exact same level of viewing. The only variation in Dr. Gray's predicted viewing for programs of the same type airing within the same quarter hour is generated by variation in the number of distant subscribers.

(30) In the next section, I demonstrate why Dr. Gray's practice of supplanting Nielsen's raw viewing data with averaged values lacks foundation and why it may also fail to correct any of the deficiencies in the underlying Nielsen data.

V.B. Dr. Gray's averaging process smooths the data, but there is no evidence that it corrects any of the deficiencies

(31) Dr. Gray's process of supplanting the actual data with averaged values acts to "smooth" (i.e., eliminate) the variation in the underlying data, but there is no evidence that this practice does anything to correct any of the known deficiencies arising from the fact that Nielsen's national survey fails to produce observed viewing data for approximately 93% of the distant signal programming hours and yields household weights that are untethered to the distant subscriber populations. To gain some intuition for Dr. Gray's process, consider the following extract showing the raw Nielsen weighted household viewing data for the syndicated television show Scrubs in July 2010.

Figure 7: Sample programs

Station	Show start time	Title	Distant viewership (Nielsen)
WGNA	7/5/2010 23:30	Scrubs	54,142
WGNA	7/12/2010 23:30	Scrubs	58,089
WGNA	7/19/2010 23:30	Scrubs	—
WGNA	7/26/2010 23:30	Scrubs	56,735

(32) This extract shows Nielsen-weighted household viewing of between 54,142 and 58,089 for three of the four airings on Sunday evenings in July 2010. Given the relative consistency of viewing for the three recorded airings, one might be tempted to assume that the missing actual viewing on July 19 was most likely similar to the actual viewing on the other three dates and to, say, replace the missing value with the average value of viewing on the other three days. While not unreasonable on its face, this approach is nevertheless questionable because, among other things, it ignores programming on other stations and the fact that such programming competes for viewers. For example, if a major television event is taking place on one station, then we might reasonably expect below average viewing of programs airing at the same time on other stations. Additionally, this approach ignores the

fact that viewing in adjacent quarter hours and in the local market may also be informative about the likely actual viewing level among households that receive programming on a distant basis.

(33) Rather than use observed viewing information to impute the missing values, as described above, or accept a missing value as a zero when the evidence supported such an assumption, Dr. Gray set the missing records equal to zero and then replaced the zero values with an average based on a combination of the actual positive viewing and imputed zeros.[25] Applying this type of averaging process to the extract for Scrubs in July 2010, for example, produces an estimate of 42,242 viewing households that is inconsistent with (and unsupported by) any of the other records.

(34) For his preferred model (i.e., Model 1), Dr. Gray not only filled in the missing viewing data with values based on averages of actual viewing and his zeros, but he also *replaced* the actual viewing records with such averages. Figure 8 shows Nielsen's weighted household viewing for the late-night talk shows airing on the three major network affiliates WCBS, WABC, and WNBC on Monday evenings in June 2010. In this figure, we see that Nightline had missing viewing records for three of the four airing dates, whereas the Late Show and The Tonight Show both had complete viewing records. Dr. Gray nevertheless replaced each of the viewing records with values based on the average among all viewing records (missing or otherwise) for programs of the same type that aired within the same quarter hour.

Figure 8: Examples of Dr. Gray's averaging process

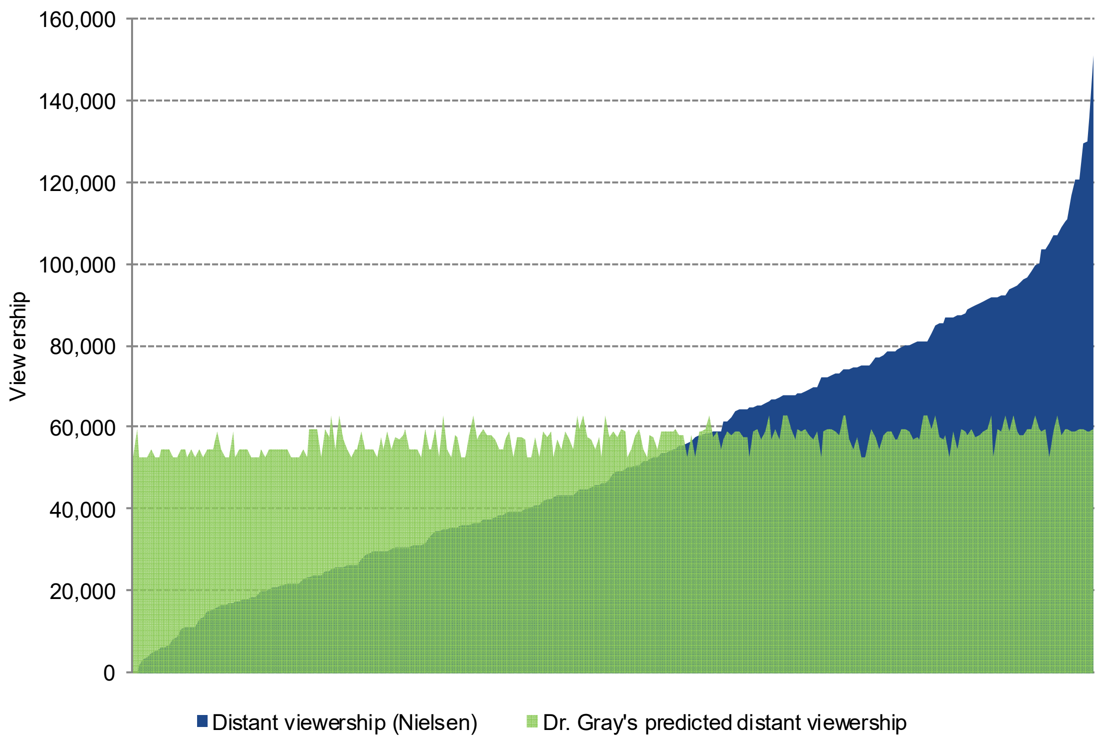
Station	Show start time	Title	Distant viewership (Nielsen)	Model 1 predicted distant viewership
WCBS	6/7/2010 23:35	Late Show With David Letterman	6,682	4,154
WCBS	6/14/2010 23:35	Late Show With David Letterman	17,762	4,154
WCBS	6/21/2010 23:35	Late Show With David Letterman	2,731	4,154
WCBS	6/28/2010 23:35	Late Show With David Letterman	11,445	4,154
WABC	6/7/2010 23:35	Nightline	—	4,246
WABC	6/14/2010 23:35	Nightline	3,084	4,246
WABC	6/21/2010 23:35	Nightline	—	4,246
WABC	6/28/2010 23:35	Nightline	—	4,246
WNBC	6/7/2010 23:35	The Tonight Show With Jay Leno	4,523	4,092
WNBC	6/14/2010 23:35	The Tonight Show With Jay Leno	4,103	4,092
WNBC	6/21/2010 23:35	The Tonight Show With Jay Leno	4,149	4,092
WNBC	6/28/2010 23:50	The Tonight Show With Jay Leno	4,141	4,092

(35) The averaging process that Dr. Gray used as part of his preferred model fills in the missing data by increasing the "zeros" and the lower-valued positive viewing records at the expense of the higher positive viewing records. Figure 9 demonstrates the broader effect of Dr. Gray's averaging process on the distant viewing of WGNA in 2010. Specifically, the data in the figure show Nielsen's raw

[25] Dr. Gray calculated averages based on only the positive viewing in his Model 2, but he supplanted all of the viewing records with these averages.

weighted household viewing for syndicated programs (blue) together with Dr. Gray's predicted viewing for each of these programs (green). These data, which are ordered on the horizontal axis from smallest to largest viewing according to Nielsen, demonstrate how Dr. Gray's preferred model redistributed viewing from the most viewed programs to the least viewed programs.

Figure 9: WGNA syndicated viewership instances in quarter hour 2, 2010



(36) Dr. Gray failed to explain why applying an averaging process to impute missing values and/or redistributing the raw Nielsen viewing data—based on sparse and incomplete data nonetheless—is appropriate or in any way corrects for the known deficiencies in the data. Dr. Gray also failed to explain that it is entirely possible for such averaging processes to leave the relative shares in the original data unchanged, even when those relative shares are flawed and unreliable.

(37) To demonstrate how an averaging process can leave the relative shares unchanged, consider the example in Figure 10 below showing hypothetical viewing of two half-hour programs, A and B. I assume for the purpose of the example that each program's episodes attract a constant number of viewers but that the raw data omit at least one viewing record.

Figure 10: Model prediction exemplar

Viewing period	Raw data		Model 1		Model 2		Model 3	
	Program A	Program B	Program A	Program B	Program A	Program B	Program A	Program B
Ep. 1 Quarter 1	10	1	3	1	4	1.33	10	1
Ep. 1 Quarter 2	-	1	3	1	4	1.33	3	1
Ep. 2 Quarter 1	1	2	3	1	4	1.33	1	2
Ep. 2 Quarter 2	1	-	3	1	4	1.33	1	1
Share of viewership	**75%**	**25%**	**75%**	**25%**	**75%**	**25%**	**75%**	**25%**

(38) According to these data, the relative viewing shares for programs A and B are 0.75 and 0.25, respectively. However, under constant viewership of each episode, there are 22 viewing instances of Program A and 6 viewing instance of Program B, which translate to relative viewing shares of 78.6% (22/28) and 21.4% (6/28). Dr. Gray's averaging processes are unable to account for such patterns in the data, produce incorrect viewing instances, and yet leave the incorrect relative shares in the raw data unchanged.

(39) Model 1, for example, maintains the original relative shares because the imputed averaged values perfectly offset the reduction caused by supplanting the actual values, thereby leaving the original total viewing numbers for each program unchanged. Alternatively, Models 2 and 3 maintain the original relative shares by adding viewing for each program in proportion to the observed positive viewing.

(40) Dr. Gray's averaging process is not only limited in its ability to properly detect patterns within programs, but it is also insensitive to imbalances in the Nielsen household weights. To see why this is the case, suppose that programs A and B were aired on different stations with the same number of subscribers. Suppose also that the sampled households received the same weight but the number of sample households receiving Program A on a distant basis is actually twice that of Program B.[26] In such a case, Dr. Gray's averaging process would again leave the relative shares unchanged and, hence, would fail to correct for the upward bias in Program A's relative share.[27]

(41) While the example above is based on hypothetical data, an examination of the Dr. Gray's preferred model shows that it largely replicates the totals (and, hence, relative shares) in the actual raw Nielsen data rather than producing new shares based on independent estimates of the missing data.[28] Figure

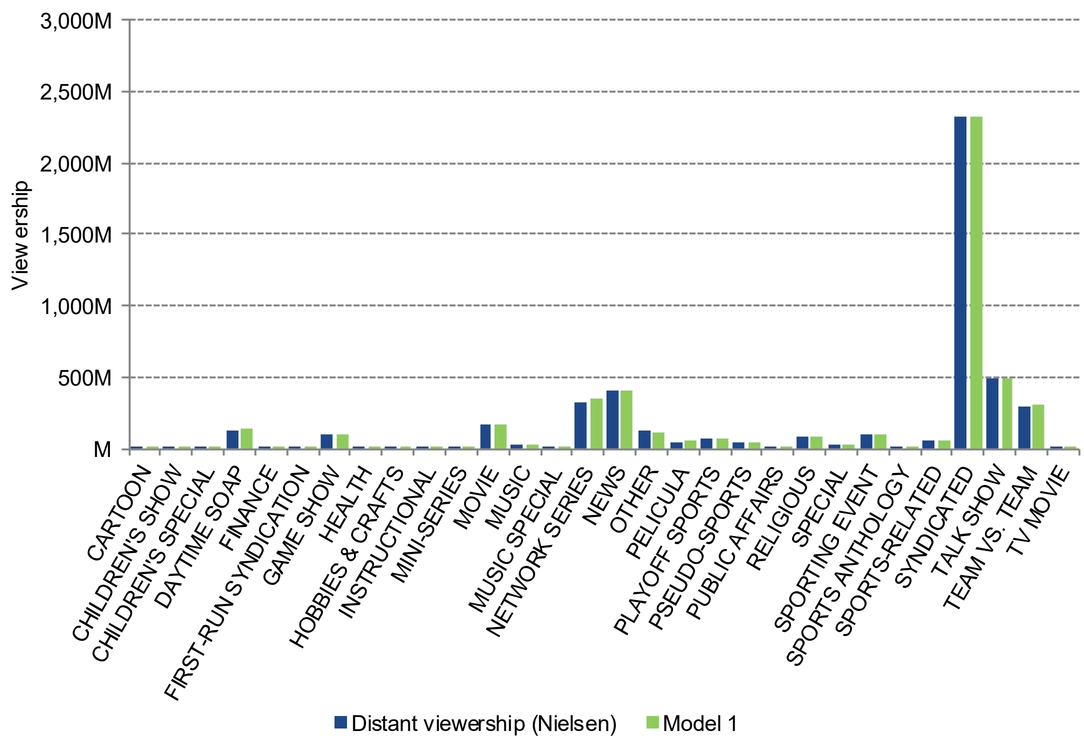
26 Note that this assumption is entirely consistent with the fact that the sampling weights provided by Nielsen are untethered to the distant subscriber populations.

27 Relative viewing of Program A is overstated because its viewing is weighted identically to Program B's despite the fact that its viewing is based on a larger number of sampled households. Dr. Gray acknowledged the existence of such imbalances in the Nielsen sample, but he is unable to properly account for such imbalances because Nielsen did not provide him with information regarding the number of households sampled in any station's distant market or the sampling mechanism that gave rise to each sampled household.

28 Appendix F contains figures on additional years, all of which provide similar results.

11, for example, shows that the totals based on Dr. Gray's averaged values from Model 1 are nearly identical to the weighted viewing totals by program category in the underlying raw Nielsen data.

Figure 11: Distant viewership (Nielsen) versus predicted (Gray Model 1) viewing—2010



(42) In summary, the consumer of Dr. Gray's viewing study is left to conclude either that (i) he successfully corrected the deficiencies in the underlying raw Nielsen data but nevertheless reached the same conclusions or (ii) that his approach was ineffectual at correcting any of the known deficiencies and left the unreliable shares based on the raw data largely unchanged.

V.C. Dr. Gray's model treats broad categories of programming as equivalent

(43) Dr. Gray relies on Gracenote's program-type categorization to estimate his models. However, Gracenote's program categorization often lumps together disparate programs from different claimant groups. Figure 12 below summarizes the number of broadcasts falling into each bucket in 2010.

Figure 12: Relationship between Gracenote's program type and Dr. Gray's categorization (2010 broadcasts)

Gracenote categorization	Gray categorization				
	Commercial	Devotional	Program supplier	JSC	Total
Cartoon	0	1	14,536	0	**14,537**
Children's show	0	0	10,137	0	**10,137**
Children's special	0	0	772	0	**772**
Daytime soap	0	0	29,013	0	**29,013**
Finance	347	0	2,324	0	**2,671**
First-run syndication	0	0	2,029	0	**2,029**
Game show	0	0	32,417	0	**32,417**
Health	68	0	1,080	0	**1,148**
Hobbies & crafts	23	0	63	0	**86**
Instructional	1	0	3,126	0	**3,127**
Mini-series	0	0	69	0	**69**
Movie	0	1	6,585	0	**6,586**
Music	102	0	2,223	0	**2,325**
Music special	25	0	585	0	**610**
Network series	0	0	43,825	0	**43,825**
News	133,301	52	38,424	0	**171,777**
Other	11,266	14	112,926	0	**124,206**
Pelicula	0	0	430	0	**430**
Playoff sports	14	0	94	1,182	**1,290**
Pseudo-sports	0	0	263	0	**263**
Public affairs	2,424	5	1,625	0	**4,054**
Religious	0	9,178	9	0	**9,187**
Special	1,296	331	3,215	0	**4,842**
Sporting event	0	0	10,258	3	**10,261**
Sports anthology	1	0	1,468	0	**1,469**
Sports-related	3,750	0	9,967	0	**13,717**
Syndicated	0	0	260,814	0	**260,814**
Talk show	0	1,206	132,331	0	**133,537**
Team vs. Team	8	0	103	4,726	**4,837**
TV movie	0	0	421	0	**421**
Total	**152,626**	**10,788**	**721,132**	**5,911**	**890,457**

(44) This figure shows that Gracenote consistently categorizes programming from multiple claimant groups within the same program-type classification. For example, the figure shows CTV programming is always grouped together with another claimant's programming.[29]

[29] There is a discrepancy between Dr. Gray's Table 5 and my own Figure 8 (from my March 22, 2019 report), both of which show claimant shares of compensable minutes of programming. It appears that the bulk of the difference is driven by the treatment of a number of news programs that aired on multiple broadcast stations. I included these in the Program Suppliers category while Dr. Gray included them in the CTV category.

(45) The figure also shows that there are 14 broadcasts of playoff sports programming in the CTV category, 94 broadcasts of playoff sports programming within the program suppliers category, and 1,182 broadcasts of playoff sports programming within the sports claimant category. Dr. Gray's predictive viewing regressions treat all the programs within Gracenote's "playoff sports" bucket identically despite the disparate nature of these programs.

(46) As can be seen in Figure 13 below, Dr. Gray's model predicts virtually the same amount of viewing for an NHL playoff game (a JSC program) as that of a high school game (a CTV program), due to the shared program type and similar distant subscriber levels.

Figure 13: "Playoff sports" within the CTV and JSC categories

Date	Station	Title	Quarter	Subscribers	Model 1 predicted viewing	Distant viewership (Nielsen)
March 13, 2010	WDCW	High school basketball	89	491,138	36,829	-
June 9, 2010	WNBC	NHL hockey	89	491,904	36,872	4,018

Similarly, Figure 14 shows that Dr. Gray predicted the same levels of distant viewing for two specials with very different levels of viewing (a PS show about Cleopatra and a CTV show airing a parade) according to Nielsen.

Figure 14: "Specials" within the PS and CTV categories

Date	Station	Title	Quarter	Subscribers	Model 1 predicted viewing	Distant viewership (Nielsen)
Sept. 4, 2010	WABC	Cleopatra: the Search for The Last Queen of Egypt	60	498,205	1,900	15,929
March 17, 2010	WNBC	St. Patrick's Day Parade	60	502,200	1,911	31,640

V.D. Dr. Gray does not treat WGNA commensurately with non-WGNA stations

(47) Because Dr. Gray scaled the average viewing according to the number of subscribers receiving individual stations on a distant basis—and otherwise treated programs within the same quarter-hour and program type identically—the number of distant subscribers plays a central role in determining the relative weight that he assigned to individual stations in his relative share calculations, with one major exception. In this section, I show how Dr. Gray failed to treat WGNA commensurately with non-WGNA stations with respect to the relative weight determination; I also show how this non-commensurate treatment biases the weights that he assigns to individual stations.

(48) First, to see the station-level effect of Dr. Gray's averaging process, it is helpful to compare his predicted viewing for each station to the underlying raw Nielsen data for each station. Figure 15 compares the results from Dr. Gray's preferred model (i.e., Model 1) to the extrapolated number of compensable distant viewing instances based on the raw Nielsen data for the top 25 distant signals by subscriber count in 2010. (See Appendix C for the full list of results.) This extract illustrates the high degree of variability of the total viewing in the raw Nielsen data relative to the "smoothed" averaging process that Dr. Gray applied to remove viewing from some stations and redistribute it to other stations.

Figure 15: Dr. Gray's Model 1 imputations for 2010 (excerpt)

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1—Nielsen)	Annual subscribers
2010	WGNA	361,669,993	363,479,159	1,809,166	21,796,480
2010	WPIX	248,821,191	256,466,782	7,645,591	1,694,132
2010	WSFL	16,987,756	143,965,925	126,978,169	868,726
2010	WABC	227,575,992	141,439,595	(86,136,397)	511,662
2010	WNBC	221,033,386	136,096,343	(84,937,043)	487,942
2010	WCBS	452,644,558	134,609,608	(318,034,949)	496,488
2010	WNYW	198,093,168	130,469,743	(67,623,425)	577,367
2010	WDCW	156,290,991	109,539,552	(46,751,439)	562,347
2010	KABC	74,426,346	108,112,279	33,685,933	376,798
2010	KCBS	97,519,868	107,466,646	9,946,778	371,200
2010	KNBC	104,858,954	107,326,643	2,467,689	367,418
2010	KTLA	36,320,964	99,137,321	62,816,357	525,721
2010	KTTV	48,477,039	97,576,429	49,099,390	421,563
2010	KTFF	103,862,582	68,690,517	(35,172,065)	203,831
2010	W21AU	—	63,971,851	63,971,851	163,476
2010	WTHR	85,379	60,223,105	60,137,726	157,573
2010	KOFY	330,192	56,831,843	56,501,651	287,256
2010	WRTV	24,831	53,524,772	53,499,941	157,576
2010	WWOR	24,424,850	53,258,134	28,833,284	212,541
2010	XETV	466,264	51,108,286	50,642,022	541,570
2010	KWGN	8,168,658	49,610,196	41,441,538	202,289
2010	WSBK	11,644,255	43,690,318	32,046,063	198,081
2010	KGO	34,605,643	41,610,398	7,004,755	105,957
2010	WLBT	15,492,580	27,898,022	12,405,442	60,067
2010	KTVU	19,689,461	21,110,816	1,421,355	51,955

(49) As a second example, consider the list for 2013 displayed in Figure 16. While the qualitative patterns in this figure are similar to those in the last figure, the first two rows reveal the disparate weighting Dr. Gray ascribed to WGNA versus non-WGNA stations. Here, we see that Dr. Gray adjusted the

aggregate viewing of WPIX so it surpassed the aggregate viewing of WGNA, despite the fact that WGNA had almost 20 times more distant subscribers.

Figure 16: Dr. Gray's Model 1 imputations for 2013 (excerpt)

Year	Station	Distant viewership (Nielsen)	Model 1	Difference (Model 1—Nielsen)	Annual subscribers
2013	WPIX	115,440,027	344,154,872	228,714,845	1,094,274
2013	WGNA	296,612,897	291,696,063	(4,916,834)	20,403,222
2013	WDCW	252,322,070	182,372,808	(69,949,262)	637,235
2013	WCBS	297,654,718	154,747,884	(142,906,834)	357,865
2013	WNBC	278,114,102	152,385,510	(125,728,592)	331,298
2013	WABC	265,773,187	150,673,869	(115,099,318)	347,276
2013	WNYW	87,738,595	131,282,498	43,543,903	371,654
2013	KABC	188,243,486	104,422,471	(83,821,015)	238,638
2013	KNBC	101,136,180	102,237,442	1,101,262	220,440
2013	KCBS	80,228,010	98,728,914	18,500,904	225,956
2013	KTTV	44,839,049	96,997,303	52,158,254	265,452
2013	KTLA	16,529,079	84,048,115	67,519,036	247,423
2013	WVLA	7,989,935	39,649,642	31,659,707	81,896
2013	KWGN	25,296,134	37,624,893	12,328,759	117,095
2013	WSFL	15,318,591	36,859,767	21,541,176	277,531
2013	WWOR	16,773,742	33,710,488	16,936,746	120,971
2013	WSBK	15,436,593	30,115,662	14,679,069	111,312
2013	WPCW	31,539,736	17,258,221	(14,281,515)	50,578
2013	KXVO	643,043	16,826,514	16,183,471	48,622
2013	WMC	-	16,755,201	16,755,201	33,419
2013	WRC	39,479,618	16,219,953	(23,259,665)	30,966
2013	WCAU	37,356,218	14,397,278	(22,958,940)	27,385
2013	WMUR	2,939,054	12,430,780	9,491,726	25,823
2013	KSHB	7,167,069	12,114,608	4,947,539	23,665
2013	KGO	6,153,306	11,968,728	5,815,422	24,275

(50) The distortion in the relative number of viewing instances introduced by Dr. Gray's separate treatment of WGNA has a direct impact on his final share allocations. This is most easily seen by noting that Dr. Gray's share calculation in a given year is mathematically equivalent to a weighted average of station-specific claimant shares where the weights are equal to the relative share of total viewing instances to a given station in said year.[30]

[30] I have included tables showing Dr. Gray's claimant shares and weights for each station in Appendix E.

(51) To see how Dr. Gray set WGNA's share in 2010, for example, consider the total number of predicted viewing instances from his non-WGNA regression. Figure 17 shows that Dr. Gray predicted a total of 3,057 million distant viewing instances with 560 million (18%) attributable to WGNA and 2,497 million (82%) attributable to non-WGNA stations. Thus, based on Dr. Gray's non-WGNA regression analysis, WGNA accounted for 18% of aggregate viewing. However, Dr. Gray did not rely on the 18% figure in his final share analysis. Instead, he replaced the 560 million figure with the lower 362 million figure that he generated from his separate WGNA regression. Plugging in this separate value, which was obtained from a separate regression with a separate scaling, reduced WGNA's relative share from 18% to 12.6%.

Figure 17: 2010 Predicted viewing instances from Dr. Gray's non-WGNA regression

Station	Predicted viewing instances	
	Non-WGNA regression	Model 1
WGNA	560,057,541	363,479,159
Non-WGNA	2,497,631,911	2,497,631,911
Total	3,057,689,452	2,861,111,070

(52) Replacing the 12.6% station weight for WGNA with the 18% weight that places WGNA on the same scale as other stations within the non-WGNA regression produces the viewing shares shown in Figure 18 below.

Figure 18: Shares based on commensurate treatment of WGNA

Year	PS	JSC	DEV	CTV
2010	68.9%	14.3%	0.8%	15.9%
2011	60.1%	16.6%	0.8%	22.6%
2012	51.9%	19.5%	0.2%	28.4%
2013	52.5%	18.8%	0.1%	28.6%
Average	**58.4%**	**17.3%**	**0.5%**	**23.9%**

(53) The analysis above highlights the sensitivity of Dr. Gray's final shares to the weights that he ascribed to individual stations. Because of the inherent unreliability in Dr. Gray's station weights, I have also performed an alternative calculation that maintains Dr. Gray's station-level shares but uses weights equal to each station's relative share of total distant subscribers. Performing this calculation yields the share listed in Figure 19 below.

Figure 19: Shares based subscriber-weighted station shares

Year	PS	JSC	DEV	CTV
2010	36.9%	26.0%	1.7%	35.4%
2011	28.4%	26.2%	1.7%	43.6%
2012	23.1%	28.5%	0.2%	48.1%
2013	22.7%	26.2%	0.1%	51.1%
Average	**27.8%**	**26.7%**	**0.9%**	**44.5%**

VI. Dr. Gray's total regressions generate nonsensical results

(54) In addition to his flawed distant viewing analysis, Dr. Gray also included a total viewing analysis in which he aggregated the weighted household viewing in the local and distant markets to create a measure of total viewing. As part of this analysis, Dr. Gray ran a linear regression relating his measure of total viewing to the program type and quarter-hour in which the program was aired. Dr. Gray then replaced his total viewing measures with the average values of total viewing for each given quarter-hour and program type as predicted by his regression.

(55) By supplanting all of the raw Nielsen data, Dr. Gray implicitly acknowledged that the raw Nielsen data are deficient and cannot be used directly to generate reliable viewing shares. However, Dr. Gray did not provide any basis or support for his practice of supplanting raw total viewing numbers, nor did he provide any evidence that this practice in any way corrected for the deficiencies in the raw data.

(56) In fact, the evidence suggests that Dr. Gray's practice of supplanting data with his averaged values is unreliable. For example, Dr. Gray's averaging process yields nonsensical predictions, including more than 100,000 instances of negative predicted viewing in each year between 2010 and 2012. The exact number of negative viewing instances is documented in Figure 20 below.

Figure 20: Negative predicted viewing occurrences in Dr. Gray's linear regression

Year	Negative predicted viewing occurrences
2010	127,344
2011	142,098
2012	140,810
2013	135,316

Figure 21 below provides an explicit example of Dr. Gray's unreliable predictions. Specifically, the figure shows total viewing of the movie "Erin Brockovich" as reported in the raw Nielsen data next to Dr. Gray's predicted viewing. The latter viewing numbers for this particular movie, which are always much lower than the viewing reported by Nielsen, drop from a high of 5,843 viewing households to a low of *negative* 2,249 viewing households.

Figure 21: Example of movie with positive and negative predicted viewing

Title	Quarter	Total viewership (Nielsen)	Gray predicted total viewership
Erin Brockovich	1	125,420	5,842
Erin Brockovich	2	104,490	3,831
Erin Brockovich	3	86,338	3,430
Erin Brockovich	4	86,338	1,966
Erin Brockovich	5	68,209	1,061
Erin Brockovich	6	41,610	504
Erin Brockovich	7	42,552	288
Erin Brockovich	8	42,552	(282)
Erin Brockovich	9	32,750	(789)
Erin Brockovich	10	30,341	(1,615)
Erin Brockovich	11	30,341	(1,559)
Erin Brockovich	12	30,341	(2,249)

In summary, Dr. Gray provides no basis or support for his imputation methodology. Moreover, his methodology produces nonsensical viewing levels and unreliable total viewing levels, and any share calculation derived from unreliable viewing levels is necessarily unreliable.

VII. Dr. Gray's 95% confidence intervals are invalid

(57) As part of his amended report, Dr. Gray added "confidence intervals for each model's calculated enhanced viewing metrics."[31] However, these intervals are calculated incorrectly and give the mistaken impression that Dr. Gray's viewership shares are precisely estimated.

(58) There are at least three fundamental problems with Dr. Gray's calculation of his confidence intervals. First, Dr. Gray artificially inflated the number of records in his databases when running his regressions. Figure 22 below shows the actual number of records in Dr. Gray's databases relative to the sample sizes that Dr. Gray used his regressions.

Figure 22: Actual quarter hours versus Dr. Gray's regression "observations"

Year	Number of WGNA quarter hours	Number of "observations" in WGNA regression	Number of non-WGNA quarter hours	Number of "observations" in non-WGNA regression
2010	35,216	525,720	2,570,059	36,999,874
2011	35,152	525,660	2,880,278	41,388,046
2012	35,260	526,920	2,840,107	40,836,844
2013	35,170	525,600	2,400,309	34,457,464

(59) The figure shows that in each of his primary regressions, Dr. Gray increased the sample sizes relative to the actual number of records (inclusive of imputed "zeros") by a factor of almost 15. Dr. Gray did this by instructing the statistical software package that he used to assume that each record in his database represented multiple observations.[32] For example, as can be seen in Figure 1, Dr. Gray instructed the statistical software package to assume that the 15,693 (weighted) households watching Sports Zone on KABC at 18:00 on January 10, 2010 should count as 15 separate observations: 15,693 households watching at 18:00, 15,693 households watching at 18:01, . . ., 15,693 households watching at 18:14. However, this assumption is demonstrably false. We know from the underlying raw Nielsen data that these 15,693 households are an extrapolated value from a single household that tuned in for only a single minute of the 15-minute quarter hour.

(60) Second, the bootstrap simulation process that Dr. Gray used to generate his confidence intervals assumes that the records in the Nielsen sample were obtained from a simple random sample. The record belies this assumption.

(61) Third, when constructing his intervals, Dr. Gray implicitly assumes that each of the individual viewing records in his database is an exact measure of the number of households viewing a particular station's programming within a given quarter hour. But the individual viewing records are anything

[31] Amended Gray Report, footnote 26.

[32] This is evident in Dr. Gray's log files. Specifically, in each call to the Poisson regression command, Dr. Gray included the command "[w=min]," which instructed Stata to assume frequency weights and explains why Stata included the parenthetical "FREQUENCY WEIGHTS ASSUMED" in the output.

but exact measures, and ignoring this source of uncertainty in his calculations leads to a false sense of precision. As is clear from Mr. Lindstrom's testimony in a prior proceeding, Mr. Lindstrom and Dr. Gray are aware of these additional sources of uncertainty and have elected to ignore them in their analyses: [33]

> JUDGE STRICKLER: And you end up with these very low numbers, and you don't know what they are, so you put in the caret or the asterisk, as you say, correct?
>
> THE WITNESS: That's correct.
>
> JUDGE STRICKLER: Is there a margin of error or a level of confidence associated with the numbers, particularly at the lower level, where you have these carets or asterisks so that we know what—I know, because the zero bound there, so we don't have a negative number of people throwing things at the television and refusing to watch it adamantly but we have either zero or some number above it. How do you statistically, if at all, how does Nielsen statistically, if at all, account for a margin of error within a certain level of confidence?
>
> THE WITNESS: We didn't produce that data for this particular report.
>
> JUDGE STRICKLER: So, so—I'm sorry. Go ahead.
>
> THE WITNESS: No, so I'm saying that I don't have that data to be able to readily identify.
>
> JUDGE STRICKLER: But Nielsen produces that sort of information as a matter of course is what you're saying?
>
> THE WITNESS: Yes, it is possible to produce that sort of data, and we do it frequently. What you would expect, and this goes back to is that, for any given station on any given quarter hour, you would expect high levels of relative error.

(62) Neither Mr. Lindstrom nor Dr. Gray provided any measures of precision associated with the underlying Nielsen estimates and so I am unable to correct any of Dr. Gray's confidence intervals. However, it is a well-known fact that properly accounting for the uncertainty in the Nielsen estimates underlying Dr. Gray's viewing records would broaden his confidence intervals.[34]

[33] Allocation Hearing Transcript of Paul Lindstrom. Volume XIII, June 3, 2013 at 301:10-303:7. Exhibit 2030.

[34] It is known that bootstrap procedures that incorrectly treat imputed values as the true observed values underestimate variance and produce invalid confidence intervals that are too narrow. *See, e.g.,* Jun Shao and Randy R. Sitter, "Bootstrap for Imputed Survey Data," *Journal of the American Statistical Association* 91, no. 435 (1996): 1278.

VIII. Relative percentage of compensable devotional programming

(63) Counsel asked me to calculate the number of distant signals retransmitted by cable and satellite systems with at least 33% devotional programming and to report the respective percentages of the total time on distant signals carried by cable systems and satellite carriers represented by Devotional category programming. Figure 23 and Figure 24 summarize the results of these calculations.

Figure 23: Proportion of distant and religious signals (cable and satellite)

Year	Number of distant signals		Number of distant religious signals		Proportion of distant religious signals	
	Cable	Satellite	Cable	Satellite	Cable	Satellite
2010	1,266	136	52	0	4.1%	0.0%
2011	1,358	106	51	0	3.8%	0.0%
2012	1,393	100	53	0	3.8%	0.0%
2013	1,425	83	56	0	3.9%	0.0%
Average	**1,361**	**106**	**53**	**0**	**3.9%**	**0.0%**

Figure 24: Share of compensable devotional programs of total compensable minutes (cable and satellite)

Year	Number of compensable minutes		Number of distant Devotional compensable minutes		Proportion of distant Devotional compensable minutes	
	Cable	Satellite	Cable	Satellite	Cable	Satellite
2010	1,851,078,382	91,125,779	78,700,257	900,480	4.3%	1.0%
2011	2,095,803,645	82,160,005	79,880,718	908,064	3.8%	1.1%
2012	2,079,079,377	84,507,669	80,678,076	897,223	3.9%	1.1%
2013	2,119,933,167	68,095,468	73,027,526	798,234	3.4%	1.2%
Average	**2,036,473,643**	**81,472,230**	**78,071,644**	**876,000**	**3.8%**	**1.1%**

IX. Satellite penetration

(64) Counsel asked me to calculate the number and percentage of satellite subscribers in each DMA that was included in the Sanders Report.[35] The results of this analysis for 2010 are displayed in Figure 25 below.[36]

Figure 25: Comparison of DMA ranking by satellite penetration rate and number of satellite subscribers – 2010

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
SHREVEPORT-TEXARKANA	59.0%	386,180	227,846	0.7%	0.7%
MERIDIAN	57.0%	72,180	41,143	0.1%	0.8%
TYLER-LONGVIEW (LUFKIN & NACOGDOCHES)	56.0%	267,890	150,018	0.4%	1.2%
COLUMBUS-TUPELO-WEST POINT	56.0%	189,460	106,098	0.3%	1.5%
PADUCAH-CAPE GIRARDEAU-HARRISBG-MT VERNON	55.0%	399,690	219,830	0.6%	2.2%
ABILENE-SWEETWATER	54.0%	116,190	62,743	0.2%	2.4%
SPRINGFIELD, MO.	53.0%	422,740	224,052	0.7%	3.0%
CHICO-REDDING	53.0%	197,970	104,924	0.3%	3.3%
COLUMBIA - JEFFERSON CITY	53.0%	178,810	94,769	0.3%	3.6%
ROANOKE-LYNCHBURG	52.0%	461,220	239,834	0.7%	4.3%
LITTLE ROCK-PINE BLUFF	51.0%	564,490	287,890	0.8%	5.2%
JACKSON, MISS.	51.0%	336,520	171,625	0.5%	5.7%
SHERMAN-ADA	51.0%	127,990	65,275	0.2%	5.9%
YAKIMA-PASCO-RICHLAND-KENNEWICK	50.0%	219,510	109,755	0.3%	6.2%
WICHITA FALLS & LAWTON	50.0%	154,450	77,225	0.2%	6.4%
TERRE HAUTE	50.0%	145,550	72,775	0.2%	6.6%
AMARILLO	48.0%	192,490	92,395	0.3%	6.9%
BOISE	47.0%	262,800	123,516	0.4%	7.2%
MEDFORD-KLAMATH FALLS	47.0%	172,900	81,263	0.2%	7.5%
JOPLIN-PITTSBURG	47.0%	155,670	73,165	0.2%	7.7%
MISSOULA	47.0%	111,940	52,612	0.2%	7.9%
QUINCY-HANNIBAL-KEOKUK	47.0%	102,710	48,274	0.1%	8.0%
FRESNO-VISALIA	46.0%	579,180	266,423	0.8%	8.8%
SPOKANE	46.0%	419,350	192,901	0.6%	9.3%
MACON	46.0%	239,330	110,092	0.3%	9.7%
MONROE-EL DORADO	46.0%	177,200	81,512	0.2%	9.9%
IDAHO FALLS-POCATELLO	46.0%	126,880	58,365	0.2%	10.1%
GREAT FALLS	46.0%	65,000	29,900	0.1%	10.2%
TWIN FALLS	46.0%	64,740	29,780	0.1%	10.2%
GREENVILLE-SPARTANBURG-ASHEVILLE-ANDRSN	45.0%	865,810	389,615	1.1%	11.4%

[35] See Appendices B, C, D, and E of the Sanders Report.

[36] Figures containing results for the remaining years are available in Appendix G.

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
BIRMINGHAM	45.0%	742,140	333,963	1.0%	12.4%
DULUTH-SUPERIOR	45.0%	174,360	78,462	0.2%	12.6%
HATTIESBURG-LAUREL	45.0%	111,610	50,225	0.1%	12.7%
CLARKSBURG-WESTON	45.0%	110,050	49,523	0.1%	12.9%
ALBUQUERQUE-SANTA FE	44.0%	694,040	305,378	0.9%	13.8%
LEXINGTON	44.0%	506,340	222,790	0.7%	14.4%
COLORADO SPRINGS-PUEBLO	44.0%	334,710	147,272	0.4%	14.9%
RENO	44.0%	270,500	119,020	0.3%	15.2%
BANGOR	44.0%	144,230	63,461	0.2%	15.4%
YUMA-EL CENTRO	44.0%	118,300	52,052	0.2%	15.6%
TRAVERSE CITY-CADILLAC	43.0%	245,000	105,350	0.3%	15.9%
SAN ANGELO	43.0%	54,580	23,469	0.1%	15.9%
MEMPHIS	42.0%	667,660	280,417	0.8%	16.8%
CHARLESTON-HUNTINGTON	42.0%	501,530	210,643	0.6%	17.4%
SALT LAKE CITY	41.0%	944,060	387,065	1.1%	18.5%
DES MOINES-AMES	41.0%	432,310	177,247	0.5%	19.0%
EVANSVILLE	41.0%	291,830	119,650	0.4%	19.4%
TALLAHASSEE-THOMASVILLE	41.0%	280,710	115,091	0.3%	19.7%
WAUSAU-RHINELANDER	41.0%	184,720	75,735	0.2%	19.9%
BEAUMONT-PORT ARTHUR	41.0%	167,330	68,605	0.2%	20.1%
LUBBOCK	41.0%	158,360	64,928	0.2%	20.3%
SAINT LOUIS	40.0%	1,249,450	499,780	1.5%	21.8%
MOBILE-PENSACOLA	40.0%	534,730	213,892	0.6%	22.4%
COLUMBIA, S.C.	40.0%	398,620	159,448	0.5%	22.9%
HUNTSVILLE-DECATUR, FLORENCE	40.0%	390,900	156,360	0.5%	23.3%
SOUTH BEND-ELKHART	40.0%	336,130	134,452	0.4%	23.7%
SAVANNAH	40.0%	322,030	128,812	0.4%	24.1%
ALBANY, GA.	40.0%	156,890	62,756	0.2%	24.3%
BUTTE-BOZEMAN	40.0%	66,260	26,504	0.1%	24.4%
DENVER	39.0%	1,539,380	600,358	1.8%	26.1%
SACRAMENTO-STOCKTON-MODESTO	39.0%	1,404,580	547,786	1.6%	27.7%
BURLINGTON-PLATTSBURGH	39.0%	330,650	128,954	0.4%	28.1%
FORT SMITH	39.0%	298,330	116,349	0.3%	28.5%
JOHNSTOWN-ALTOONA	39.0%	294,350	114,797	0.3%	28.8%
OTTUMWA-KIRKSVILLE	39.0%	51,370	20,034	0.1%	28.9%
ATLANTA	38.0%	2,387,520	907,258	2.7%	31.5%
NASHVILLE	38.0%	1,019,010	387,224	1.1%	32.7%
TUCSON (NOGALES)	38.0%	465,100	176,738	0.5%	33.2%
WACO-TEMPLE-BRYAN	38.0%	339,570	129,037	0.4%	33.6%
GREENVILLE-NEW BERN-WASHINGTON	38.0%	290,700	110,466	0.3%	33.9%
MONTEREY-SALINAS	38.0%	227,390	86,408	0.3%	34.1%
DALLAS-FT. WORTH	37.0%	2,544,410	941,432	2.8%	36.9%
TULSA	37.0%	528,070	195,386	0.6%	37.5%
TRI-CITIES, TENN.-VA.	37.0%	334,620	123,809	0.4%	37.8%
LINCOLN & HASTINGS-KEARNEY, PLUS	37.0%	281,590	104,188	0.3%	38.1%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
JACKSON, TENN.	37.0%	98,250	36,353	0.1%	38.2%
ALEXANDRIA, LA.	37.0%	90,740	33,574	0.1%	38.3%
CHARLOTTESVILLE	37.0%	75,920	28,090	0.1%	38.4%
PRESQUE ISLE	37.0%	31,070	11,496	0.0%	38.5%
PHOENIX	36.0%	1,873,930	674,615	2.0%	40.4%
CHAMPAIGN & SPRINGFIELD-DECATUR	36.0%	384,620	138,463	0.4%	40.8%
FORT WAYNE	36.0%	273,860	98,590	0.3%	41.1%
SANTA BARBARA-SANTA MARIA-SAN LUIS OBISPO	36.0%	241,370	86,893	0.3%	41.4%
DOTHAN	36.0%	101,840	36,662	0.1%	41.5%
HARRISONBURG	36.0%	93,400	33,624	0.1%	41.6%
GREENWOOD-GREENVILLE, MS	36.0%	70,350	25,326	0.1%	41.7%
WILKES-BARRE-SCRANTON	35.0%	593,480	207,718	0.6%	42.3%
RICHMOND-PETERSBURG	35.0%	553,950	193,883	0.6%	42.8%
KNOXVILLE	35.0%	552,380	193,333	0.6%	43.4%
DAVENPORT-ROCK ISLAND-MOLINE	35.0%	308,910	108,119	0.3%	43.7%
LANSING	35.0%	253,690	88,792	0.3%	44.0%
EUGENE	35.0%	241,730	84,606	0.2%	44.2%
LAFAYETTE, LA.	35.0%	230,180	80,563	0.2%	44.5%
BAKERSFIELD	35.0%	222,910	78,019	0.2%	44.7%
LA CROSSE-EAU CLAIRE	35.0%	214,820	75,187	0.2%	44.9%
BILLINGS	35.0%	107,420	37,597	0.1%	45.0%
CASPER-RIVERTON	35.0%	55,620	19,467	0.1%	45.1%
LOS ANGELES	34.0%	5,659,170	1,924,118	5.6%	50.7%
CHARLOTTE	34.0%	1,147,910	390,289	1.1%	51.9%
JACKSONVILLE	34.0%	679,120	230,901	0.7%	52.5%
MADISON	34.0%	377,260	128,268	0.4%	52.9%
CHATTANOOGA	34.0%	365,400	124,236	0.4%	53.3%
FARGO-VALLEY CITY	34.0%	240,330	81,712	0.2%	53.5%
SIOUX CITY	34.0%	154,810	52,635	0.2%	53.7%
CHEYENNE-SCOTTSBLUFF-STERLING	34.0%	54,710	18,601	0.1%	53.7%
RALEIGH-DURHAM	33.0%	1,107,820	365,581	1.1%	54.8%
GRAND RAPIDS-KALAMAZOO-BATTLE CREEK	33.0%	740,430	244,342	0.7%	55.5%
BUFFALO	33.0%	633,220	208,963	0.6%	56.1%
FORT MYERS-NAPLES	33.0%	500,110	165,036	0.5%	56.6%
GREEN BAY-APPLETON	33.0%	443,420	146,329	0.4%	57.0%
MONTGOMERY	33.0%	244,750	80,768	0.2%	57.3%
GAINESVILLE	33.0%	128,400	42,372	0.1%	57.4%
GRAND JUNCTION-MONTROSE	33.0%	75,030	24,760	0.1%	57.5%
NEW ORLEANS	32.0%	633,930	202,858	0.6%	58.1%
CEDAR RAPIDS-WATERLOO & DUBUQUE	32.0%	346,030	110,730	0.3%	58.4%
AUGUSTA	32.0%	255,950	81,904	0.2%	58.6%
TOPEKA	32.0%	180,090	57,629	0.2%	58.8%
ERIE	32.0%	156,520	50,086	0.1%	58.9%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
MINOT-BISMARCK-DICKINSON (WILLISTON)	32.0%	136,540	43,693	0.1%	59.1%
JONESBORO	32.0%	82,300	26,336	0.1%	59.2%
NORTH PLATTE	32.0%	15,350	4,912	0.0%	59.2%
GREENSBORO-HIGH POINT-WINSTON-SALEM	31.0%	691,380	214,328	0.6%	59.8%
EL PASO	31.0%	310,760	96,336	0.3%	60.1%
PEORIA-BLOOMINGTON	31.0%	247,830	76,827	0.2%	60.3%
CORPUS CHRISTI	31.0%	199,560	61,864	0.2%	60.5%
ROCKFORD	31.0%	189,160	58,640	0.2%	60.7%
ROCHESTER-MASON CITY-AUSTIN	31.0%	144,300	44,733	0.1%	60.8%
ODESSA-MIDLAND	31.0%	143,710	44,550	0.1%	60.9%
RAPID CITY	31.0%	98,240	30,454	0.1%	61.0%
OKLAHOMA CITY	30.0%	694,030	208,209	0.6%	61.6%
FLINT-SAGINAW-BAY CITY	30.0%	458,020	137,406	0.4%	62.0%
HARLINGEN-WESLACO-BROWNSVILLE-MCALLEN	30.0%	354,150	106,245	0.3%	62.3%
BLUEFIELD-BECKLEY-OAK HILL	30.0%	142,570	42,771	0.1%	62.5%
VICTORIA	30.0%	31,560	9,468	0.0%	62.5%
HELENA	30.0%	27,630	8,289	0.0%	62.5%
ALPENA	30.0%	17,420	5,226	0.0%	62.5%
MIAMI-FT. LAUDERDALE	29.0%	1,538,090	446,046	1.3%	63.8%
PORTLAND, ORE.	29.0%	1,188,770	344,743	1.0%	64.8%
CHARLESTON, S.C.	29.0%	311,190	90,245	0.3%	65.1%
WILMINGTON	29.0%	189,950	55,086	0.2%	65.3%
LAKE CHARLES	29.0%	95,900	27,811	0.1%	65.4%
SAINT JOSEPH	29.0%	48,440	14,048	0.0%	65.4%
CHICAGO	28.0%	3,501,010	980,283	2.9%	68.3%
HOUSTON	28.0%	2,123,460	594,569	1.7%	70.0%
INDIANAPOLIS	28.0%	1,119,760	313,533	0.9%	70.9%
SAN ANTONIO	28.0%	830,000	232,400	0.7%	71.6%
WEST PALM BEACH-FT. PIERCE	28.0%	776,080	217,302	0.6%	72.2%
LOUISVILLE	28.0%	668,310	187,127	0.5%	72.8%
WICHITA1-HUTCHINSON, PLUS	28.0%	452,710	126,759	0.4%	73.2%
FLORENCE-MYRTLE BEACH	28.0%	287,400	80,472	0.2%	73.4%
SIOUX FALLS (MITCHELL)	28.0%	261,100	73,108	0.2%	73.6%
PANAMA CITY	28.0%	147,440	41,283	0.1%	73.7%
SAN FRANCISCO-OAKLAND-SAN JOSE	27.0%	2,503,400	675,918	2.0%	75.7%
CINCINNATI	27.0%	918,670	248,041	0.7%	76.4%
BATON ROUGE	27.0%	326,890	88,260	0.3%	76.7%
COLUMBUS, GA.	27.0%	213,880	57,748	0.2%	76.9%
ELMIRA	27.0%	95,790	25,863	0.1%	76.9%
LAFAYETTE, IND.	27.0%	66,180	17,869	0.1%	77.0%
WASHINGTON, D.C.	26.0%	2,335,040	607,110	1.8%	78.8%
MINNEAPOLIS-ST. PAUL	26.0%	1,732,050	450,333	1.3%	80.1%
HARRISBURG-LANCASTER-LEBANON-YORK	26.0%	743,420	193,289	0.6%	80.7%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
LAS VEGAS	26.0%	721,780	187,663	0.6%	81.2%
AUSTIN, TEX.	26.0%	678,730	176,470	0.5%	81.7%
TOLEDO	26.0%	423,100	110,006	0.3%	82.1%
WHEELING-STEUBENVILLE	26.0%	133,110	34,609	0.1%	82.2%
MARQUETTE	26.0%	88,490	23,007	0.1%	82.2%
LAREDO	26.0%	69,790	18,145	0.1%	82.3%
BEND	26.0%	66,980	17,415	0.1%	82.3%
EUREKA	26.0%	61,090	15,883	0.0%	82.4%
ORLANDO-DAYTONA BEACH-MELBOURNE	25.0%	1,455,620	363,905	1.1%	83.4%
PORTLAND-AUBURN	25.0%	408,120	102,030	0.3%	83.7%
BILOXI-GULFPORT	25.0%	122,740	30,685	0.1%	83.8%
ZANESVILLE	25.0%	32,350	8,088	0.0%	83.9%
GLENDIVE	25.0%	3,940	985	0.0%	83.9%
YOUNGSTOWN	24.0%	266,560	63,974	0.2%	84.0%
CLEVELAND	23.0%	1,520,750	349,773	1.0%	85.1%
PITTSBURGH	23.0%	1,154,950	265,639	0.8%	85.9%
KANSAS CITY	23.0%	941,360	216,513	0.6%	86.5%
NORFOLK-PORTSMOUTH-NEWPORT NEWS	23.0%	709,880	163,272	0.5%	87.0%
DAYTON	23.0%	482,590	110,996	0.3%	87.3%
PALM SPRINGS	23.0%	161,110	37,055	0.1%	87.4%
BINGHAMTON	23.0%	137,240	31,565	0.1%	87.5%
WATERTOWN	23.0%	93,970	21,613	0.1%	87.6%
BOWLING GREEN	23.0%	81,650	18,780	0.1%	87.6%
PARKERSBURG	23.0%	64,060	14,734	0.0%	87.7%
OMAHA	22.0%	410,350	90,277	0.3%	87.9%
LIMA	22.0%	71,380	15,704	0.0%	88.0%
MANKATO	22.0%	52,230	11,491	0.0%	88.0%
SEATTLE-TACOMA	21.0%	1,833,990	385,138	1.1%	89.1%
COLUMBUS, OHIO	21.0%	904,030	189,846	0.6%	89.7%
SALISBURY	21.0%	158,340	33,251	0.1%	89.8%
DETROIT	20.0%	1,890,220	378,044	1.1%	90.9%
BALTIMORE	20.0%	1,093,170	218,634	0.6%	91.5%
ANCHORAGE	20.0%	151,470	30,294	0.1%	91.6%
UTICA	20.0%	104,890	20,978	0.1%	91.7%
ALBANY-SCHENECTADY-TROY	18.0%	554,070	99,733	0.3%	92.0%
ROCHESTER, N.Y.	18.0%	392,190	70,594	0.2%	92.2%
PHILADELPHIA	17.0%	2,955,190	502,382	1.5%	93.7%
SYRACUSE	17.0%	385,440	65,525	0.2%	93.8%
TAMPA-ST. PETERSBURG, SARASOTA	16.0%	1,805,810	288,930	0.8%	94.7%
MILWAUKEE	16.0%	901,790	144,286	0.4%	95.1%
HARTFORD & NEW HAVEN	14.0%	1,010,630	141,488	0.4%	95.5%
SPRINGFIELD-HOLYOKE	14.0%	262,960	36,814	0.1%	95.6%
NEW YORK	13.0%	7,493,530	974,159	2.9%	98.5%
BOSTON	13.0%	2,410,180	313,323	0.9%	99.4%
SAN DIEGO	13.0%	1,073,390	139,541	0.4%	99.8%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
PROVIDENCE-NEW BEDFORD	10.0%	619,610	61,961	0.2%	100.0%

Appendix A. Average annual household viewing minutes per quarter hour (Nielsen data)

Figure 26: Average annual household distant viewing minutes per quarter hour—2010

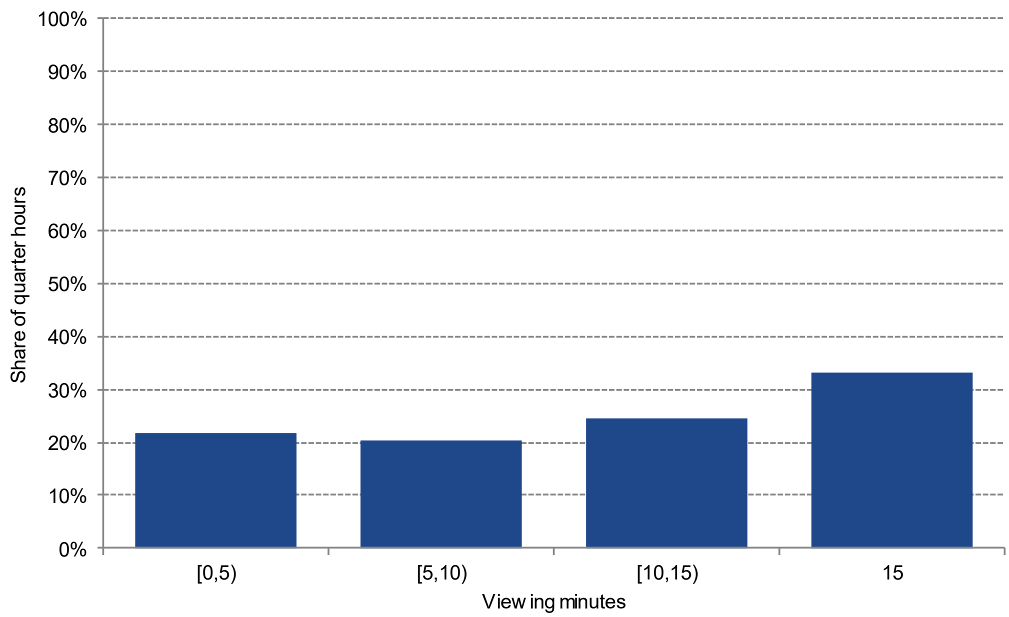


Figure 27: Average annual household distant viewing minutes per quarter hour—2011

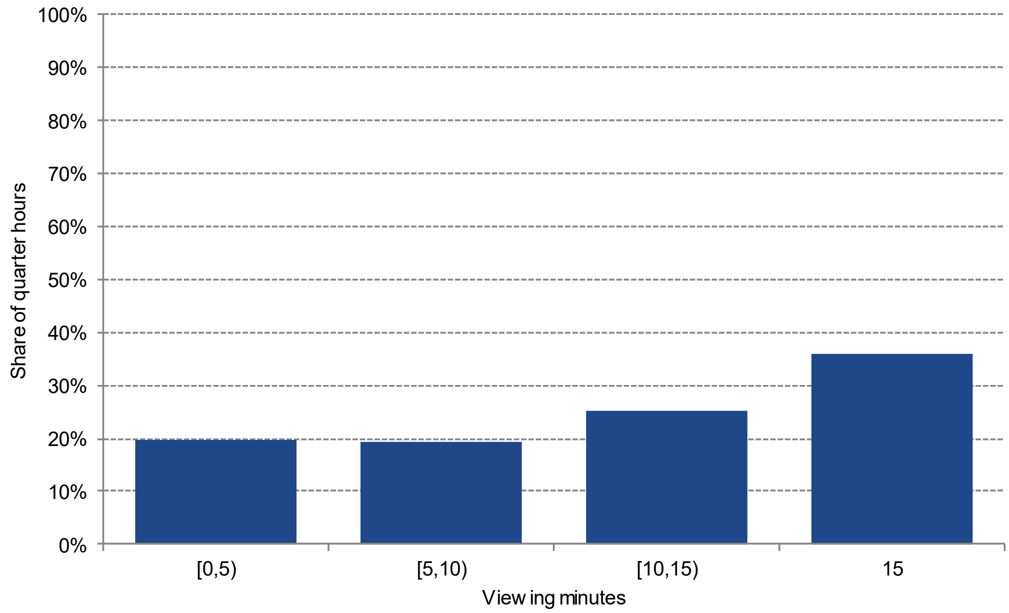


Figure 28: Average annual household distant viewing minutes per quarter hour—2012

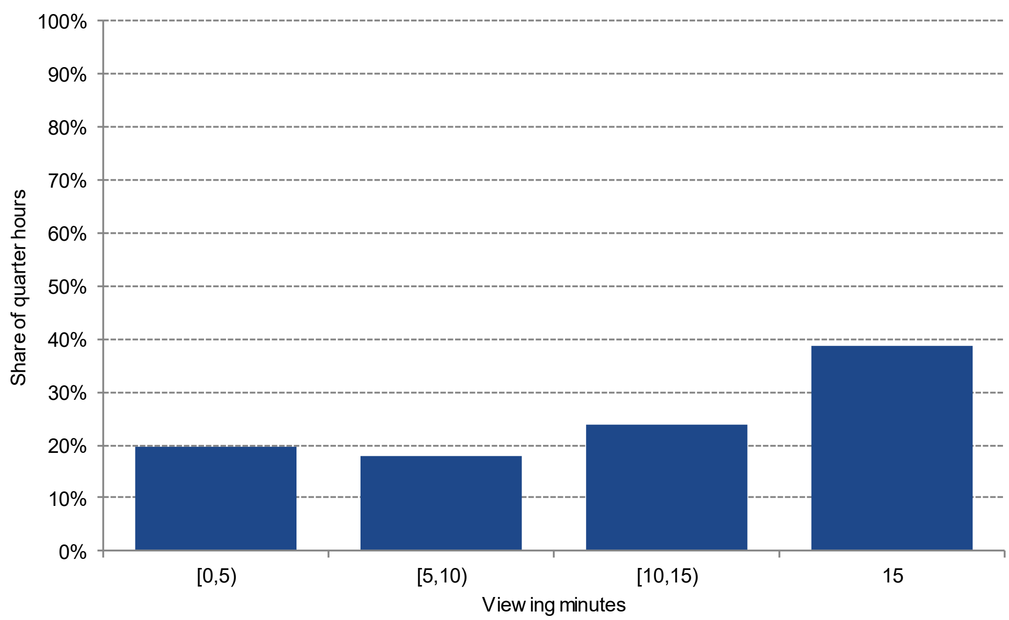
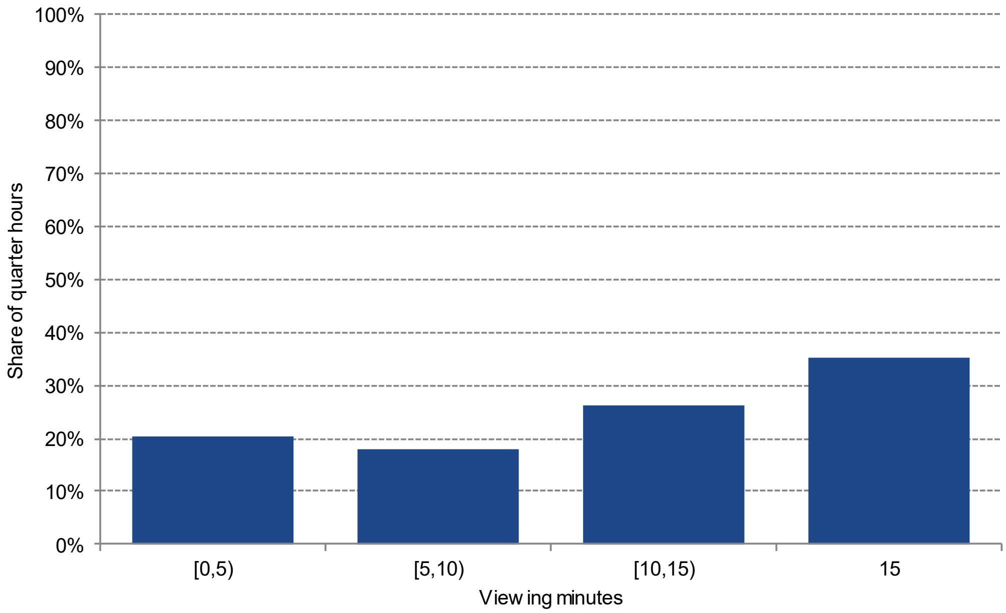
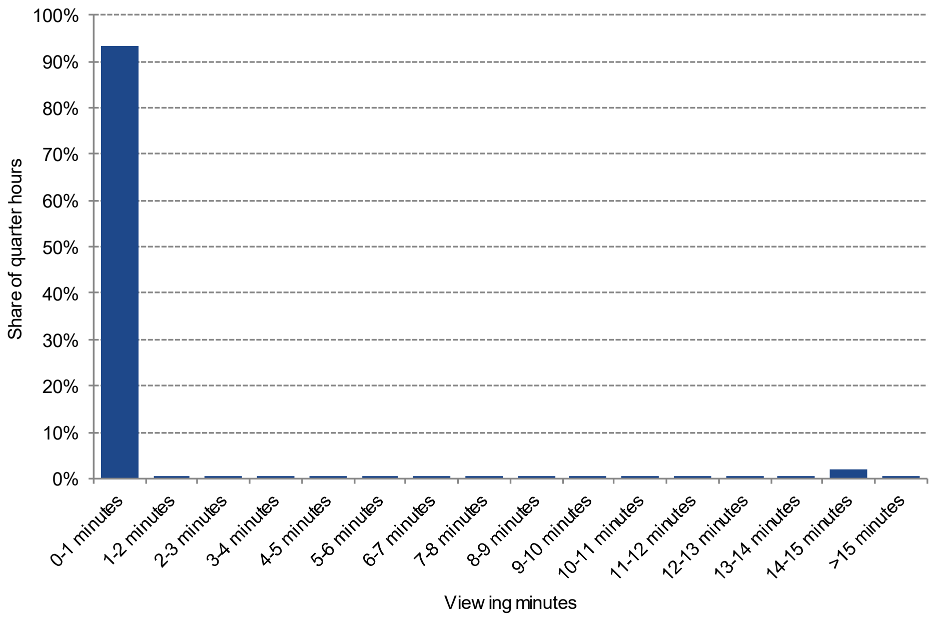


Figure 29: Average annual household distant viewing minutes per quarter hour—2013



Appendix B. Proportion of quarter hours by distant viewing minutes (Dr. Gray's regression data)[37]

Figure 30: Proportion of quarter hours by distant viewing minutes—2010



[37] The "0-1 minutes" bucket includes all instances without any Nielsen viewing data.

Figure 31: Proportion of quarter hours by distant viewing minutes—2011

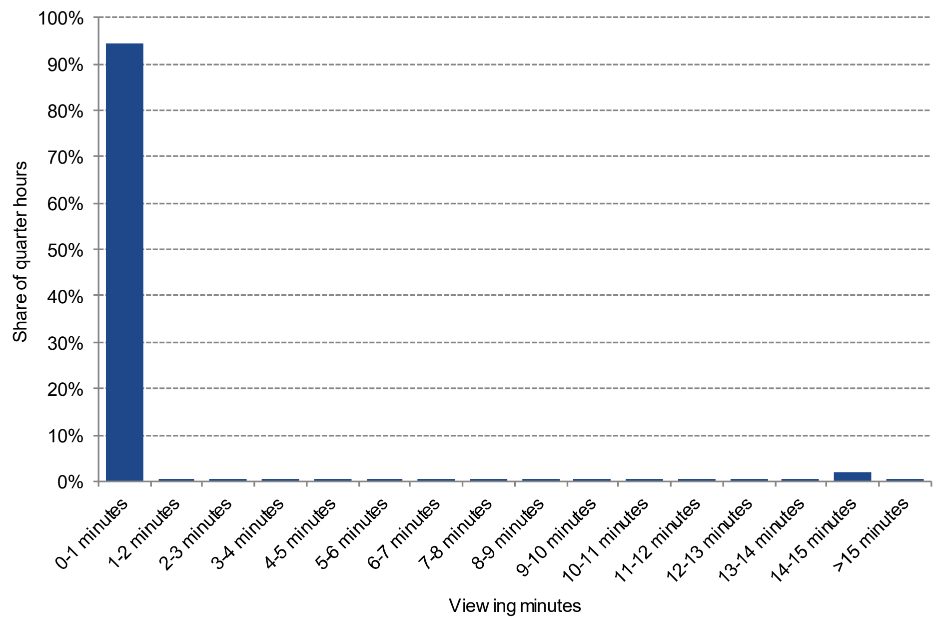


Figure 32: Proportion of quarter hours by distant viewing minutes—2012

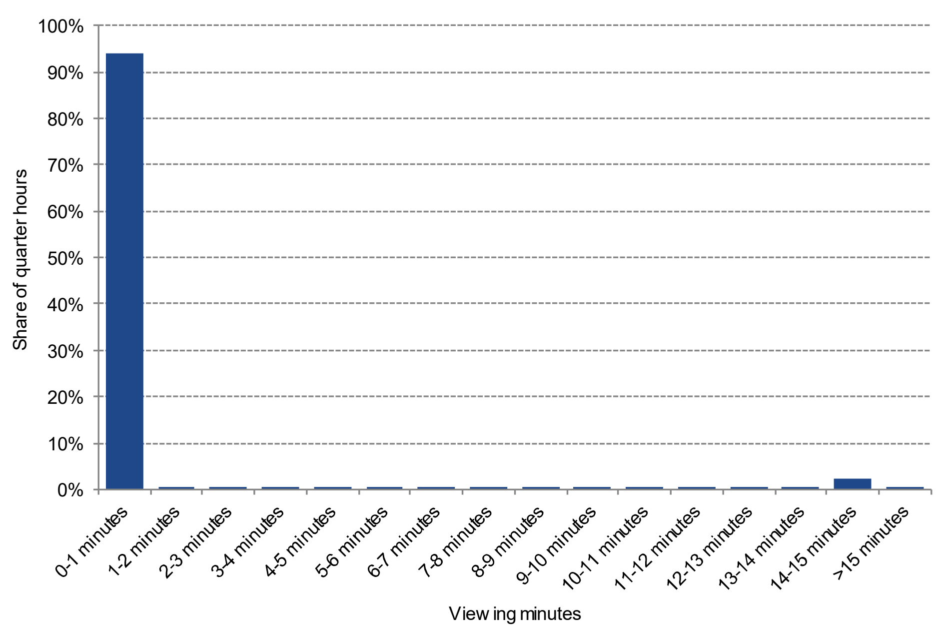
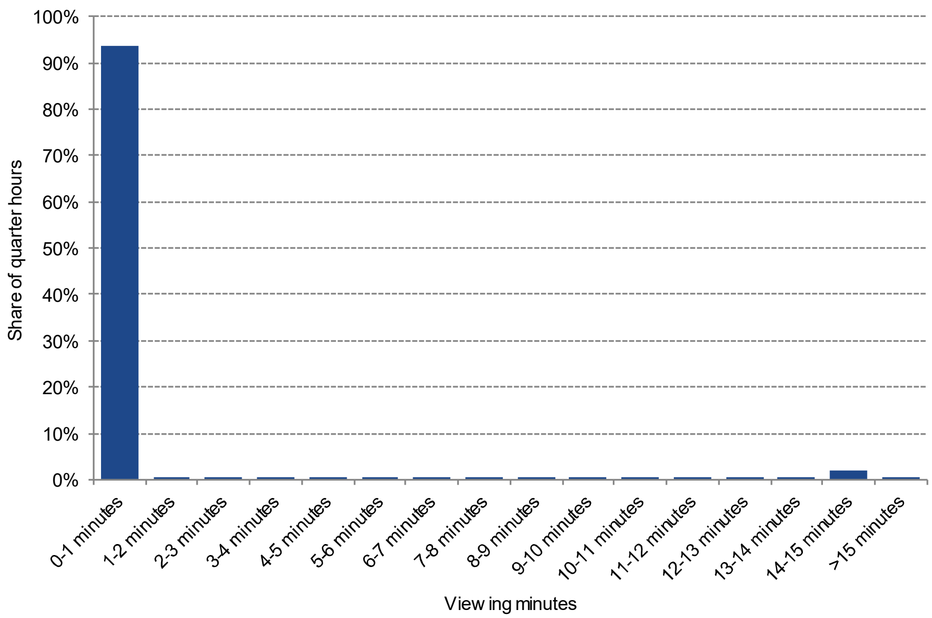


Figure 33: Proportion of quarter hours by distant viewing minutes—2013



Appendix C. Average annual household counts per quarter hour (Nielsen data)

Figure 34: Proportion of quarter hours by distant household count (Nielsen data)—2011

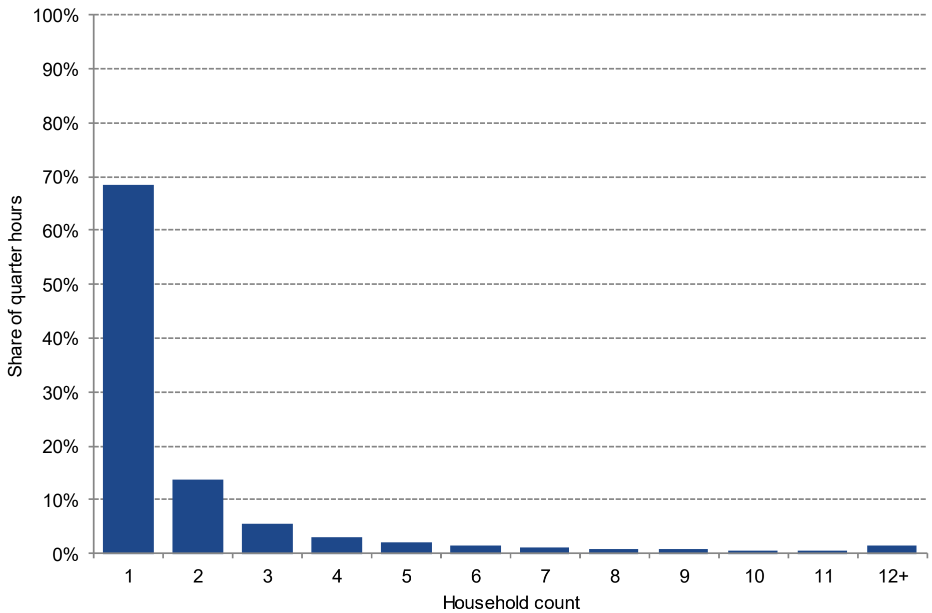


Figure 35: Proportion of quarter hours by distant household count (Nielsen data)—2012

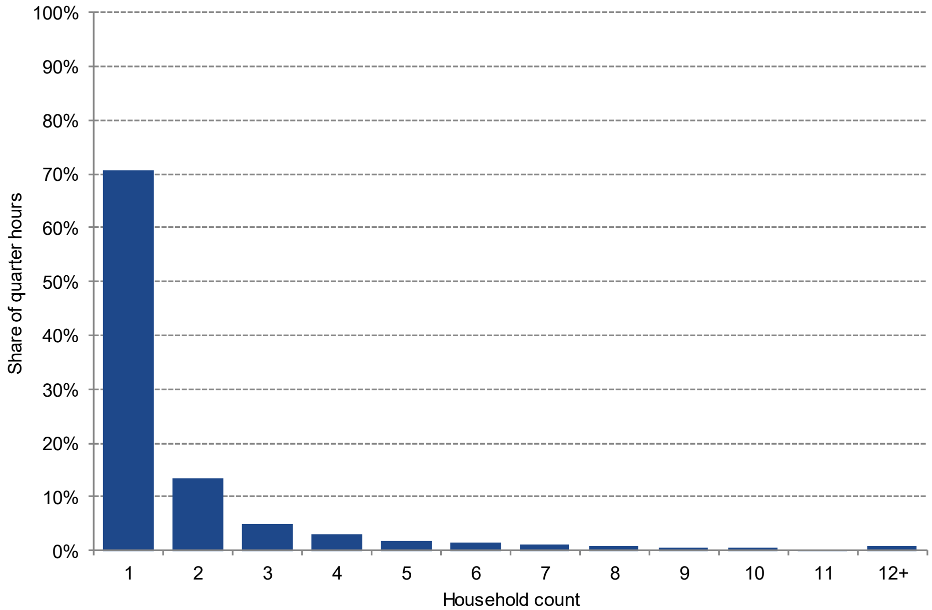
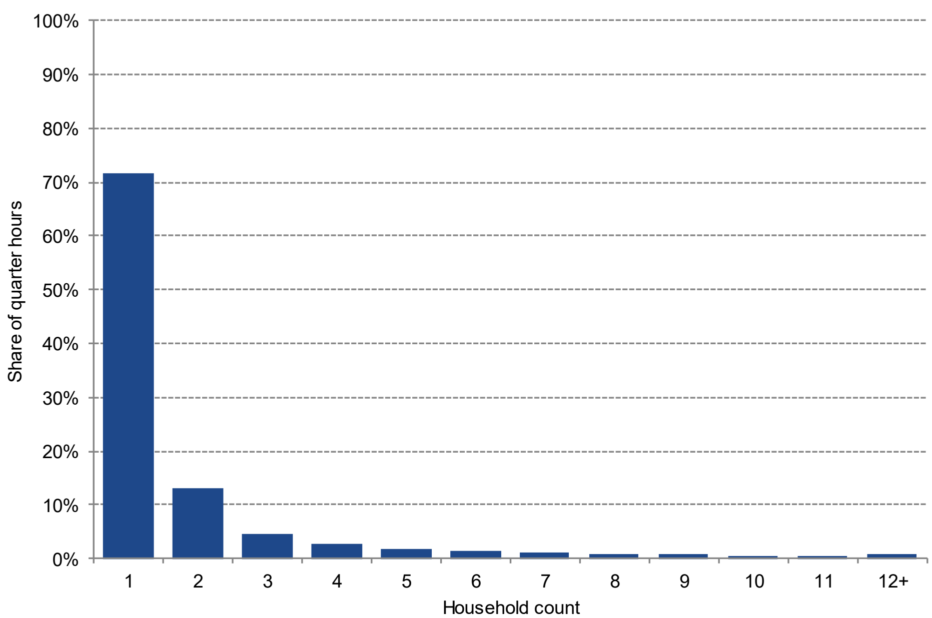


Figure 36: Proportion of quarter hours by distant household count (Nielsen data)—2013



Appendix D. Difference between Nielsen raw distant viewing and Gray Model 1 prediction, by station and year

Figure 37: Appendix A. Difference between Nielsen raw distant viewing and Gray Model 1 prediction, by station and year

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2010	WGNA	361,669,993	363,479,159	1,809,166	21,796,480
2010	WPIX	248,821,191	256,466,782	7,645,591	1,694,132
2010	WSFL	16,987,756	143,965,925	126,978,169	868,726
2010	WABC	227,575,992	141,439,595	(86,136,397)	511,662
2010	WNBC	221,033,386	136,096,343	(84,937,043)	487,942
2010	WCBS	452,644,558	134,609,608	(318,034,949)	496,488
2010	WNYW	198,093,168	130,469,743	(67,623,425)	577,367
2010	WDCW	156,290,991	109,539,552	(46,751,439)	562,347
2010	KABC	74,426,346	108,112,279	33,685,933	376,798
2010	KCBS	97,519,868	107,466,646	9,946,778	371,200
2010	KNBC	104,858,954	107,326,643	2,467,689	367,418
2010	KTLA	36,320,964	99,137,321	62,816,357	525,721
2010	KTTV	48,477,039	97,576,429	49,099,390	421,563
2010	KTFF	103,862,582	68,690,517	(35,172,065)	203,831
2010	W21AU	—	63,971,851	63,971,851	163,476
2010	WTHR	85,379	60,223,105	60,137,726	157,573
2010	KOFY	330,192	56,831,843	56,501,651	287,256
2010	WRTV	24,831	53,524,772	53,499,941	157,576
2010	WWOR	24,424,850	53,258,134	28,833,284	212,541
2010	XETV	466,264	51,108,286	50,642,022	541,570
2010	KWGN	8,168,658	49,610,196	41,441,538	202,289
2010	WSBK	11,644,255	43,690,318	32,046,063	198,081
2010	KGO	34,605,643	41,610,398	7,004,755	105,957
2010	WLBT	15,492,580	27,898,022	12,405,442	60,067
2010	KTVU	19,689,461	21,110,816	1,421,355	51,955
2010	KPIX	14,899,499	21,076,347	6,176,848	43,517
2010	KNTV	13,022,420	20,629,266	7,606,846	39,201
2010	KMAX	19,199,761	15,941,365	(3,258,396)	42,390
2010	WTIC	93,903	14,765,317	14,671,414	30,705
2010	WPCW	29,853,616	14,312,810	(15,540,806)	39,809
2010	WNUV	803,448	14,077,816	13,274,368	95,418
2010	KSKN	3,264,674	12,017,331	8,752,657	45,528
2010	KSWB	216,361	11,371,658	11,155,297	62,356
2010	WMUR	49,067,797	9,102,414	(39,965,383)	14,301
2010	KREN	—	6,972,879	6,972,879	38,273
2010	WRC	5,221,338	6,920,443	1,699,105	20,154

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2010	WUSA	11,567,961	6,800,398	(4,767,563)	20,155
2010	KSAT	139,661	6,704,013	6,564,352	10,045
2010	WNNE	4,160	6,606,586	6,602,426	8,463
2010	WCAX	108,251	6,383,308	6,275,057	8,463
2010	WVNY	16,452	6,005,886	5,989,434	8,464
2010	KARE	344,289	5,879,659	5,535,370	7,355
2010	WXIN	100,199	5,410,379	5,310,180	8,301
2010	WBNS	1,257,362	5,365,929	4,108,567	6,364
2010	KSTP	162,656	5,225,201	5,062,545	7,355
2010	WDSU	16,784	5,032,562	5,015,778	13,986
2010	WFFF	3,892	4,973,274	4,969,382	8,472
2010	WWL	2,888,337	4,969,979	2,081,642	13,987
2010	WSYX	574,458	4,847,952	4,273,494	6,364
2010	KMSP	546,596	4,431,840	3,885,244	6,702
2010	WTTE	871,518	4,344,132	3,472,614	6,364
2010	WTOK	—	4,250,321	4,250,321	10,606
2010	WJTV	12,735,430	4,032,771	(8,702,659)	4,546
2010	WTTV	1,673,897	3,889,117	2,215,220	6,743
2010	WAPT	45,435,289	3,860,422	(41,574,867)	4,546
2010	WGBC	2,858,863	3,648,495	789,632	10,606
2010	WICS	1,134,638	3,412,563	2,277,925	45,492
2010	WMC	13,552	3,346,850	3,333,298	7,890
2010	WREG	123,869	3,175,993	3,052,124	7,890
2010	KSHB	100,396	3,147,695	3,047,299	6,928
2010	KEYT	470,630	2,912,700	2,442,070	36,674
2010	WHBQ	3,256,308	2,870,350	(385,958)	7,891
2010	WPSD	67,997	2,664,853	2,596,856	5,503
2010	WNOL	—	2,527,191	2,527,191	7,901
2010	KFVS	48,206	2,435,359	2,387,153	5,503
2010	KCNC	6,616,587	2,435,199	(4,181,388)	2,617
2010	WTVY	46,382	2,377,144	2,330,762	24,610
2010	KUSA	7,058,714	2,351,668	(4,707,046)	2,570
2010	KMGH	—	2,348,640	2,348,640	2,593
2010	KFDM	25,988	2,174,175	2,148,187	4,528
2010	WKTV	—	2,092,330	2,092,330	4,327
2010	KBMT	43,685	2,075,587	2,031,902	4,528
2010	WJHG	—	2,036,070	2,036,070	19,379
2010	KFXF	—	1,963,175	1,963,175	3,469
2010	KDVR	5,800,022	1,908,475	(3,891,547)	2,696
2010	WVII	59,457	1,843,747	1,784,290	3,407
2010	WLBZ	29,192	1,815,840	1,786,648	3,407
2010	WBOY	19,623	1,775,341	1,755,718	3,209
2010	WVLA	112,497	1,756,701	1,644,204	16,889
2010	WDTV	11,107,974	1,664,238	(9,443,736)	3,209
2010	KCTV	468,596	1,593,566	1,124,970	2,910
2010	KTVD	12,264	1,590,450	1,578,186	2,506

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2010	WHAG	3,712	1,487,528	1,483,816	2,825
2010	WLS	—	1,462,059	1,462,059	3,122
2010	WDAF	18,329	1,406,687	1,388,358	3,032
2010	WJXX	93,854	1,344,165	1,250,311	4,177
2010	WWNY	32,635	1,293,595	1,260,960	2,743
2010	KOLN	112,275	1,167,260	1,054,985	1,958
2010	WCAU	10,291	1,144,576	1,134,285	13,152
2010	KHOU	4,251,033	1,070,519	(3,180,514)	1,733
2010	WBBM	10,720,286	1,048,209	(9,672,077)	2,083
2010	KARK	11,823,012	1,036,829	(10,786,183)	2,136
2010	WCWJ	20,575	1,030,237	1,009,662	3,810
2010	WKEF	1,516,145	1,029,020	(487,125)	11,012
2010	WMAQ	8,954,941	999,834	(7,955,107)	1,890
2010	WFLD	5,439,774	984,408	(4,455,366)	2,154
2010	WBDT	307,523	741,218	433,695	9,147
2010	WJRT	190,186	727,238	537,052	1,084
2010	WEYI	94,471	726,171	631,700	1,084
2010	WSEE	6,961,787	612,644	(6,349,143)	402
2010	WTVJ	9,341	576,054	566,713	402
2010	WPLG	25,451	566,013	540,562	402
2010	KTBY	—	556,418	556,418	2,744
2010	KOCO	49,200	458,697	409,497	5,982
2010	WXIA	882,845	402,719	(480,126)	1,224
2010	WGCL	202,462	393,692	191,230	1,163
2010	WSB	1,142,819	307,554	(835,265)	1,105
2010	WBNX	—	302,660	302,660	2,513
2010	WBNG	—	293,123	293,123	4,003
2010	WPTZ	—	220,535	220,535	469
2010	KOTA	—	202,930	202,930	187
2010	KEVN	—	158,425	158,425	187
2011	WGNA	365,555,439	368,628,922	3,073,483	21,775,297
2011	WPIX	135,955,041	232,555,508	96,600,467	1,539,134
2011	WSFL	19,216,719	216,807,715	197,590,996	1,537,300
2011	WABC	244,141,321	127,185,447	(116,955,874)	439,267
2011	WCBS	378,519,627	117,536,036	(260,983,591)	429,337
2011	WNBC	234,636,642	115,681,838	(118,954,804)	410,685
2011	WNYW	148,733,526	110,057,384	(38,676,142)	488,804
2011	KTLA	17,442,099	97,149,568	79,707,469	516,833
2011	KABC	146,194,820	93,910,819	(52,284,001)	306,122
2011	XETV	462,389	88,503,509	88,041,120	515,466
2011	KCBS	105,046,298	86,164,424	(18,881,874)	299,833
2011	KNBC	60,235,546	85,942,879	25,707,333	293,459
2011	KTTV	51,184,061	79,886,786	28,702,725	343,603
2011	WDCW	185,016,200	72,274,209	(112,741,991)	424,959
2011	KWGN	10,009,210	33,220,421	23,211,211	154,189
2011	WWOR	35,719,413	32,406,246	(3,313,167)	153,659

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2011	KGO	35,036,881	29,822,135	(5,214,746)	75,789
2011	WSBK	9,064,357	28,156,607	19,092,250	156,689
2011	WLBT	11,876,382	25,590,268	13,713,886	62,601
2011	WNUV	704,953	16,815,340	16,110,387	160,476
2011	KTVU	7,263,580	13,189,949	5,926,369	33,645
2011	KPIX	5,931,822	13,158,286	7,226,464	29,092
2011	WTVY	303,869	13,128,097	12,824,228	26,655
2011	KNTV	5,721,954	12,903,171	7,181,217	26,634
2011	WTIC	170,401	12,447,053	12,276,652	30,533
2011	WRC	8,552,656	12,384,780	3,832,124	24,760
2011	WDSU	778,249	11,999,004	11,220,755	24,094
2011	WICS	8,203,310	11,929,526	3,726,216	44,597
2011	WUSA	21,843,600	11,915,013	(9,928,587)	24,760
2011	WWL	1,519,695	11,530,274	10,010,579	24,094
2011	KMAX	7,685,597	11,239,731	3,554,134	35,928
2011	WJHG	3,752,013	10,347,820	6,595,807	19,485
2011	KXVO	1,603,797	9,706,291	8,102,494	35,055
2011	WTOK	3,468,588	9,352,374	5,883,786	17,464
2011	WVLA	620,540	9,296,127	8,675,587	17,553
2011	KSAT	1,016,447	8,272,787	7,256,340	15,847
2011	WCAU	2,891,979	8,140,478	5,248,499	15,015
2011	WMUR	16,430,130	8,050,225	(8,379,905)	14,856
2011	WTHR	1,414,637	7,748,641	6,334,004	13,151
2011	WGBC	5,945,433	7,667,067	1,721,634	17,464
2011	WMC	1,615,318	7,423,514	5,808,196	13,061
2011	KSHB	1,726,202	7,394,575	5,668,373	12,751
2011	WRTV	314,295	7,050,722	6,736,427	13,152
2011	WREG	656,410	7,049,022	6,392,612	13,061
2011	WXIN	—	6,434,523	6,434,523	13,151
2011	WNOL	1,339,991	6,305,411	4,965,420	19,986
2011	WPSD	294,423	5,989,135	5,694,712	9,770
2011	WLFL	2,964,377	5,862,447	2,898,070	30,208
2011	WNNE	—	5,803,303	5,803,303	9,396
2011	WHBQ	2,323,927	5,800,389	3,476,462	13,062
2011	KARE	9,184	5,601,111	5,591,927	9,035
2011	WBNS	1,200,609	5,501,881	4,301,272	8,805
2011	KFVS	439,123	5,476,419	5,037,296	9,769
2011	WCAX	1,552,565	5,469,577	3,917,012	9,396
2011	WVNY	1,739,403	5,299,129	3,559,726	9,396
2011	KSTP	95,461	5,205,932	5,110,471	9,035
2011	WSYX	520,879	5,151,765	4,630,886	8,806
2011	KFDM	108,215	4,805,225	4,697,010	7,640
2011	KBMT	99,842	4,519,903	4,420,061	7,640
2011	WKTV	623,147	4,516,225	3,893,078	7,369
2011	WFFF	21,235	4,161,694	4,140,459	9,363
2011	WBDT	3,485,996	3,955,588	469,592	11,088

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2011	WLBZ	4,064,128	3,936,363	(127,765)	5,699
2011	KCTV	547,571	3,884,261	3,336,690	6,163
2011	WVII	1,651,436	3,863,573	2,212,137	5,699
2011	WTTE	795,158	3,859,113	3,063,955	7,492
2011	KEYT	195,510	3,756,238	3,560,728	36,621
2011	WKEF	3,082,532	3,731,156	648,624	9,556
2011	WHAG	2,180,830	3,591,608	1,410,778	5,497
2011	WBNG	—	3,579,509	3,579,509	5,600
2011	WBNX	31,341	3,414,411	3,383,070	9,013
2011	WDAF	537,445	3,368,149	2,830,704	6,164
2011	WDTV	952,107	3,281,671	2,329,564	5,068
2011	KMSP	1,804	3,245,525	3,243,721	6,361
2011	WTTV	4,214,623	3,242,005	(972,618)	8,547
2011	WAPT	83,431,986	3,146,126	(80,285,860)	4,535
2011	WJTV	17,089,272	3,103,650	(13,985,622)	4,536
2011	WGNO	219,719	2,365,840	2,146,121	13,444
2011	KOLN	69,804	2,356,373	2,286,569	3,228
2011	KFXF	—	2,329,292	2,329,292	4,490
2011	KHOU	5,607,700	1,984,261	(3,623,439)	2,884
2011	KALB	—	1,685,009	1,685,009	8,479
2011	WBOY	228,399	1,681,576	1,453,177	4,761
2011	WJXX	43,335	1,618,599	1,575,264	5,976
2011	WJRT	569,048	1,469,322	900,274	1,824
2011	WEYI	1,052,385	1,458,471	406,086	1,823
2011	WSMV	508,452	1,351,448	842,996	6,647
2011	WTVF	1,381,961	1,293,580	(88,381)	6,647
2011	WHEC	1,205,663	1,252,181	46,518	5,950
2011	WPTZ	6,594	989,620	983,026	1,031
2011	WNAB	132,763	872,625	739,862	6,067
2011	WTVH	—	666,982	666,982	6,899
2011	WLMT	594,258	658,961	64,703	5,694
2011	KHGI	—	637,707	637,707	3,703
2011	WWHO	—	595,814	595,814	3,939
2011	KBSI	184,641	406,643	222,002	5,009
2011	KOTA	—	375,340	375,340	316
2011	KEVN	—	271,174	271,174	316
2011	WCWJ	4,337	232,340	228,003	5,707
2012	WGNA	333,841,971	333,987,989	146,018	21,502,212
2012	WPIX	121,031,897	304,417,940	183,386,043	1,135,621
2012	WNBC	273,628,273	160,432,639	(113,195,634)	360,417
2012	WCBS	272,679,181	147,854,827	(124,824,354)	391,139
2012	WNYW	157,519,207	142,023,942	(15,495,265)	414,288
2012	WABC	311,324,908	138,492,256	(172,832,652)	371,803
2012	WDCW	163,309,152	134,215,437	(29,093,715)	524,947
2012	KNBC	51,726,529	115,893,559	64,167,030	260,258
2012	KTTV	67,476,374	103,240,032	35,763,658	307,594

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2012	KABC	160,524,675	101,449,384	(59,075,291)	266,520
2012	KCBS	115,692,674	97,607,386	(18,085,288)	256,064
2012	KTLA	15,755,329	93,761,027	78,005,698	310,178
2012	WSFL	33,196,891	82,820,351	49,623,460	282,364
2012	KWGN	15,250,685	39,619,699	24,369,014	134,921
2012	WWOR	27,041,533	38,471,179	11,429,646	141,476
2012	WSBK	13,515,778	33,969,380	20,453,602	128,586
2012	WLBT	16,438,257	21,872,556	5,434,299	43,039
2012	WVLA	6,227,163	21,275,413	15,048,250	41,007
2012	WRC	30,372,293	16,190,257	(14,182,036)	28,871
2012	WPCW	19,036,880	15,485,900	(3,550,980)	48,268
2012	KSHB	6,711,603	15,048,582	8,336,979	27,966
2012	WMC	1,874,279	13,865,732	11,991,453	24,813
2012	KXVO	921,452	13,715,169	12,793,717	42,796
2012	KGO	5,074,419	13,574,508	8,500,089	29,812
2012	WCAU	34,277,038	13,116,379	(21,160,659)	23,173
2012	WTVY	175,087	13,113,400	12,938,313	36,572
2012	KNTV	5,391,252	12,348,433	6,957,181	21,823
2012	KTVU	17,399,170	11,742,459	(5,656,711)	27,291
2012	WUSA	21,760,760	11,622,179	(10,138,581)	23,935
2012	WJHG	6,509,261	11,259,640	4,750,379	19,944
2012	KPIX	16,761,295	11,000,717	(5,760,578)	23,715
2012	WLFL	4,301,251	10,991,849	6,690,598	32,647
2012	KMAX	3,560,313	10,667,843	7,107,530	29,132
2012	WPSD	488,198	10,564,991	10,076,793	18,077
2012	XETV	1,283,947	8,965,760	7,681,813	69,388
2012	WTHR	928,685	8,886,727	7,958,042	14,696
2012	WMUR	—	8,797,307	8,797,307	18,446
2012	WREG	868,797	8,060,941	7,192,144	16,324
2012	KSAT	35,545,470	8,055,100	(27,490,370)	16,961
2012	KALB	13,228	7,943,196	7,929,968	13,242
2012	WDSU	614,981	7,377,407	6,762,426	28,260
2012	WXIN	2,687,802	7,338,484	4,650,682	15,120
2012	WRTV	190,606	7,204,027	7,013,421	15,223
2012	WHBQ	1,079,547	7,114,152	6,034,605	16,324
2012	WNOL	1,695,317	7,023,248	5,327,931	20,044
2012	WSYX	54,503	6,462,147	6,407,644	13,522
2012	WNNE	5,634	6,404,073	6,398,439	10,420
2012	KLAX	5,630,978	6,310,881	679,903	13,242
2012	KCTV	188,504	6,265,291	6,076,787	12,222
2012	WHEC	4,046,737	6,201,458	2,154,721	10,088
2012	WBNS	205,562	6,185,246	5,979,684	11,473
2012	KRNSCD	—	6,183,229	6,183,229	25,289
2012	WBDT	5,742,803	6,145,493	402,690	16,592
2012	KARE	20,199	6,125,918	6,105,719	9,946
2012	WLMT	6,975,081	5,696,626	(1,278,455)	14,407

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2012	WKTV	16,778,950	5,456,352	(11,322,598)	9,129
2012	WCAX	1,796,354	5,433,532	3,637,178	10,420
2012	WHAG	3,078,540	5,226,933	2,148,393	8,573
2012	WBNX	—	5,062,328	5,062,328	13,799
2012	WVNY	355,772	4,970,341	4,614,569	10,420
2012	KFVS	2,355,230	4,917,188	2,561,958	9,630
2012	KSTP	2,038	4,846,358	4,844,320	9,946
2012	WTOK	11,697,201	4,798,837	(6,898,364)	20,408
2012	WLBZ	69,549,765	4,759,788	(64,789,977)	7,327
2012	WWL	81,951	4,740,729	4,658,778	20,232
2012	WTVH	—	4,710,226	4,710,226	9,331
2012	WFFF	7,787	4,633,384	4,625,597	10,409
2012	KLFY	161,952	4,581,250	4,419,298	9,089
2012	KATC	—	4,411,487	4,411,487	9,089
2012	WTTE	132,487	4,037,709	3,905,222	8,213
2012	WVII	17,537,701	3,866,458	(13,671,243)	7,327
2012	WBNG	28,692	3,810,285	3,781,593	7,068
2012	WTTV	814,845	3,476,995	2,662,150	9,180
2012	WGNO	600,293	3,393,494	2,793,201	15,078
2012	KBSI	115,266	3,335,288	3,220,022	7,002
2012	WJTV	1,602,438	2,647,379	1,044,941	4,564
2012	WAPT	17,173,537	2,500,789	(14,672,748)	4,564
2012	KFXF	198,869	2,273,301	2,074,432	4,725
2012	KOLN	5,530,733	2,254,926	(3,275,807)	3,949
2012	WWHO	13,312	2,214,255	2,200,943	5,309
2012	WDAF	—	2,208,734	2,208,734	9,577
2012	WSMV	403,959	2,149,661	1,745,702	9,410
2012	WDTV	1,273,305	2,129,258	855,953	5,946
2012	KHGI	23,866	1,839,393	1,815,527	3,945
2012	WBOY	1,735,826	1,816,524	80,698	5,925
2012	WEYI	527,203	1,666,447	1,139,244	2,478
2012	WCHS	—	1,596,255	1,596,255	6,179
2012	WNAB	206,126	1,491,128	1,285,002	9,371
2012	WPTZ	—	1,476,796	1,476,796	2,083
2012	WGBC	8,629	1,457,873	1,449,244	19,930
2012	WJRT	694,446	1,405,366	710,920	2,479
2012	KTMF	—	866,745	866,745	21,870
2012	KEYC	55,499	429,175	373,676	664
2012	WTIC	22,266	407,394	385,128	9,838
2012	KFDM	15,500	395,262	379,762	8,684
2012	KBMT	49,403	347,288	297,885	8,684
2012	WISE	—	343,204	343,204	6,325
2012	KOTA	—	285,066	285,066	413
2012	KEVN	—	235,847	235,847	413
2012	WNKY	13,299	172,918	159,619	1,489
2013	WPIX	115,440,027	344,154,872	228,714,845	1,094,274

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2013	WGNA	296,612,897	291,696,063	(4,916,834)	20,403,222
2013	WDCW	252,322,070	182,372,808	(69,949,262)	637,235
2013	WCBS	297,654,718	154,747,884	(142,906,834)	357,865
2013	WNBC	278,114,102	152,385,510	(125,728,592)	331,298
2013	WABC	265,773,187	150,673,869	(115,099,318)	347,276
2013	WNYW	87,738,595	131,282,498	43,543,903	371,654
2013	KABC	188,243,486	104,422,471	(83,821,015)	238,638
2013	KNBC	101,136,180	102,237,442	1,101,262	220,440
2013	KCBS	80,228,010	98,728,914	18,500,904	225,956
2013	KTTV	44,839,049	96,997,303	52,158,254	265,452
2013	KTLA	16,529,079	84,048,115	67,519,036	247,423
2013	WVLA	7,989,935	39,649,642	31,659,707	81,896
2013	KWGN	25,296,134	37,624,893	12,328,759	117,095
2013	WSFL	15,318,591	36,859,767	21,541,176	277,531
2013	WWOR	16,773,742	33,710,488	16,936,746	120,971
2013	WSBK	15,436,593	30,115,662	14,679,069	111,312
2013	WPCW	31,539,736	17,258,221	(14,281,515)	50,578
2013	KXVO	643,043	16,826,514	16,183,471	48,622
2013	WMC	—	16,755,201	16,755,201	33,419
2013	WRC	39,479,618	16,219,953	(23,259,665)	30,966
2013	WCAU	37,356,218	14,397,278	(22,958,940)	27,385
2013	WMUR	2,939,054	12,430,780	9,491,726	25,823
2013	KSHB	7,167,069	12,114,608	4,947,539	23,665
2013	KGO	6,153,306	11,968,728	5,815,422	24,275
2013	WPSD	280,442	11,059,011	10,778,569	20,866
2013	KPIX	11,606,318	10,059,644	(1,546,674)	20,123
2013	KNTV	8,968,158	10,027,152	1,058,994	18,553
2013	KTVU	8,207,594	9,491,389	1,283,795	22,586
2013	WLFL	3,345,358	9,041,907	5,696,549	34,886
2013	WTHR	252,088	9,020,525	8,768,437	16,298
2013	KMAX	10,127,953	8,940,272	(1,187,681)	23,844
2013	WREG	17,255	8,472,942	8,455,687	16,973
2013	KSAT	41,320,228	8,411,480	(32,908,748)	17,249
2013	KALB	—	8,411,226	8,411,226	16,401
2013	WLMT	5,351,171	8,291,022	2,939,851	21,377
2013	WNOL	36,793	8,273,530	8,236,737	23,225
2013	WRTV	145,771	7,853,797	7,708,026	16,298
2013	KLAX	20,455,103	7,788,979	(12,666,124)	16,401
2013	WXIN	7,953,310	7,298,338	(654,972)	16,298
2013	WSYX	946,611	7,152,563	6,205,952	14,794
2013	KCTV	7,270,162	7,133,553	(136,609)	13,973
2013	WTVH	—	7,055,296	7,055,296	14,455
2013	WHEC	15,260,450	6,990,942	(8,269,508)	12,932
2013	WHBQ	—	6,834,084	6,834,084	16,973
2013	WBDT	1,601,522	6,534,729	4,933,207	18,822
2013	WNNE	—	5,926,597	5,926,597	10,493

Year	Station	Distant viewership (Nielsen)	Model1	Difference (Model 1 - Nielsen)	Annual subscribers
2013	KRNSCD	—	5,773,017	5,773,017	17,332
2013	KARE	2,972,558	5,748,371	2,775,813	10,426
2013	WBNX	470,963	5,742,803	5,271,840	16,747
2013	WHAG	29,664	5,543,491	5,513,827	10,273
2013	WCAX	4,084,779	5,510,123	1,425,344	10,493
2013	WKTV	—	5,208,456	5,208,456	9,711
2013	WVNY	666,033	5,054,326	4,388,293	10,493
2013	KSTP	9,621,331	5,039,236	(4,582,095)	10,426
2013	KLFY	35,660	5,001,471	4,965,811	9,235
2013	KATC	56,601	4,838,393	4,781,792	9,235
2013	WBNS	3,994,891	4,836,826	841,935	8,743
2013	WLBZ	145,122	4,658,944	4,513,822	8,086
2013	KFVS	2,622,361	4,599,643	1,977,282	9,023
2013	WJHG	1,508,971	4,286,929	2,777,958	20,105
2013	WVII	39,601	4,227,505	4,187,904	8,087
2013	WFFF	30,430	4,066,631	4,036,201	10,493
2013	KBSI	1,088,284	3,917,372	2,829,088	9,023
2013	WTTE	539,175	3,912,302	3,373,127	8,743
2013	WCHS	342,597	3,287,765	2,945,168	6,533
2013	WTTV	402,292	3,222,741	2,820,449	9,565
2013	WUSA	5,889,023	2,786,323	(3,102,700)	10,644
2013	WBNG	2,976,715	2,668,704	(308,011)	7,727
2013	WJTV	8,567,207	2,569,157	(5,998,050)	4,553
2013	WLBT	—	2,512,485	2,512,485	4,553
2013	WWHO	81,410	2,462,345	2,380,935	6,050
2013	WAPT	7,888,749	2,427,014	(5,461,735)	4,553
2013	WEYI	294,412	1,654,195	1,359,783	2,934
2013	KOLN	2,009,521	1,451,509	(558,012)	3,966
2013	WPTZ	—	1,341,676	1,341,676	2,182
2013	WJRT	43,613	874,637	831,024	2,868
2013	KHGI	361,470	781,599	420,129	3,984
2013	KEYC	67,836	425,289	357,453	715
2013	KOTA	—	281,462	281,462	460
2013	KEVN	—	211,878	211,878	460
2013	KFXF	699,284	122,742	(576,542)	1,676

Appendix E. Dr. Gray's claimant and station shares based on Gray's Model 1

Figure 38: Claimant and station shares based on Dr. Gray's Model 1

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2010	WGNA	21,796,466	17.5%	2.4%	40.2%	39.9%	12.7%
2010	WPIX	1,694,132	78.5%	0.1%	6.3%	15.2%	9.0%
2010	WSFL	868,726	95.2%	0.0%	4.6%	0.3%	5.0%
2010	WNYW	577,372	66.8%	0.5%	15.8%	16.9%	4.6%
2010	WDCW	562,347	92.9%	0.7%	3.4%	3.0%	3.8%
2010	KTLA	525,721	74.1%	0.4%	1.4%	24.1%	3.5%
2010	WABC	511,674	78.9%	0.0%	10.9%	10.1%	4.9%
2010	WCBS	496,490	77.3%	0.0%	14.9%	7.9%	4.7%
2010	WNBC	487,942	81.3%	0.0%	9.8%	8.9%	4.8%
2010	KTTV	421,567	71.1%	0.2%	11.5%	17.2%	3.4%
2010	KABC	376,809	75.6%	0.0%	9.4%	15.0%	3.8%
2010	KCBS	371,201	77.3%	0.0%	12.2%	10.5%	3.8%
2010	KNBC	367,416	83.3%	0.0%	7.5%	9.1%	3.8%
2010	KOFY	287,256	80.5%	4.6%	2.3%	12.6%	2.0%
2010	XETV	271,489	81.6%	3.5%	0.0%	14.9%	1.8%
2010	WWOR	212,538	84.6%	4.1%	7.6%	3.7%	1.9%
2010	KWGN	202,289	82.5%	0.5%	3.6%	13.4%	1.7%
2010	WSBK	198,082	89.3%	0.0%	4.0%	6.6%	1.5%
2010	W21AU	163,477	91.7%	0.0%	8.3%	0.0%	2.2%
2010	WRTV	157,574	76.7%	0.3%	12.0%	11.0%	1.9%
2010	WTHR	157,574	80.6%	0.0%	8.8%	10.6%	2.1%
2010	KGO	105,962	79.1%	0.0%	9.4%	11.5%	1.5%
2010	KTFF	68,725	95.1%	0.8%	3.5%	0.6%	2.4%
2010	WLBT	60,067	79.0%	0.3%	9.4%	11.3%	1.0%
2010	KTVU	51,956	72.1%	0.2%	10.3%	17.4%	0.7%
2010	WNUV	47,709	86.5%	2.9%	10.0%	0.5%	0.5%
2010	KPIX	43,517	75.6%	0.0%	12.2%	12.2%	0.7%
2010	KMAX	42,390	82.7%	0.0%	5.6%	11.6%	0.6%
2010	WPCW	39,809	83.2%	1.3%	2.1%	13.4%	0.5%
2010	KNTV	39,201	79.1%	0.0%	11.2%	9.7%	0.7%
2010	KSKN	34,146	95.3%	0.0%	0.6%	4.1%	0.4%
2010	KSWB	31,178	77.1%	0.2%	7.1%	15.6%	0.4%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2010	WTIC	30,705	69.1%	0.1%	15.7%	15.0%	0.5%
2010	WMUR	14,301	75.3%	0.0%	13.3%	11.3%	0.3%
2010	WRC	11,597	71.7%	0.0%	12.4%	15.9%	0.2%
2010	WUSA	11,597	78.1%	0.2%	10.6%	11.1%	0.2%
2010	KSAT	10,044	77.4%	0.5%	12.0%	10.0%	0.2%
2010	KREN	9,568	96.2%	0.0%	3.8%	0.0%	0.2%
2010	WFFF	8,472	74.0%	0.2%	17.0%	8.8%	0.2%
2010	WCAX	8,463	78.0%	0.1%	13.9%	8.0%	0.2%
2010	WNNE	8,463	84.0%	0.1%	9.0%	6.9%	0.2%
2010	WVNY	8,463	83.5%	0.5%	12.5%	3.5%	0.2%
2010	WXIN	8,301	65.8%	0.0%	16.3%	18.0%	0.2%
2010	WDSU	7,734	75.7%	0.0%	13.0%	11.3%	0.2%
2010	WWL	7,734	75.8%	0.0%	12.2%	11.9%	0.2%
2010	WICS	7,586	74.5%	0.4%	15.4%	9.7%	0.1%
2010	KARE	7,355	79.2%	0.2%	10.0%	10.6%	0.2%
2010	KSTP	7,355	70.2%	0.0%	12.6%	17.1%	0.2%
2010	WTTV	6,743	94.4%	0.1%	2.0%	3.5%	0.1%
2010	KMSP	6,702	61.5%	0.2%	14.4%	23.8%	0.2%
2010	WBNS	6,364	75.9%	0.0%	14.0%	10.1%	0.2%
2010	WSYX	6,364	78.0%	0.2%	12.5%	9.3%	0.2%
2010	WTTE	6,364	72.9%	0.6%	17.3%	9.2%	0.2%
2010	KEYT	6,123	77.4%	0.0%	12.3%	10.2%	0.1%
2010	WGBC	5,919	78.4%	0.0%	20.0%	1.6%	0.1%
2010	WTOK	5,919	79.3%	0.7%	13.1%	6.9%	0.1%
2010	WNOL	4,609	95.1%	0.8%	2.8%	1.4%	0.1%
2010	WAPT	4,546	80.0%	0.5%	11.2%	8.2%	0.1%
2010	WJTV	4,546	76.1%	0.3%	15.6%	8.0%	0.1%
2010	WHBQ	4,400	60.7%	0.4%	19.0%	19.9%	0.1%
2010	WMC	4,400	75.7%	0.2%	12.9%	11.2%	0.1%
2010	WREG	4,400	74.6%	0.4%	10.9%	14.0%	0.1%
2010	WTVY	4,101	75.1%	0.2%	16.1%	8.6%	0.1%
2010	KSHB	3,873	78.6%	0.0%	11.4%	9.9%	0.1%
2010	WJHG	3,228	76.6%	0.6%	13.8%	8.9%	0.1%
2010	KFVS	3,073	82.7%	0.2%	10.8%	6.3%	0.1%
2010	WPSD	3,073	77.5%	0.3%	13.4%	8.8%	0.1%
2010	WVLA	2,814	79.6%	0.4%	14.5%	5.5%	0.1%
2010	KFXF	2,547	86.0%	0.6%	13.0%	0.4%	0.1%
2010	KDVR	2,539	69.7%	0.2%	13.2%	16.8%	0.1%
2010	KBMT	2,509	77.7%	0.7%	13.8%	7.8%	0.1%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2010	KFDM	2,509	77.0%	2.7%	10.7%	9.6%	0.1%
2010	KCNC	2,460	76.3%	0.0%	12.8%	10.9%	0.1%
2010	KMGH	2,438	76.9%	0.0%	10.6%	12.5%	0.1%
2010	WKTV	2,423	79.6%	0.1%	11.7%	8.6%	0.1%
2010	KUSA	2,417	78.9%	0.0%	8.3%	12.8%	0.1%
2010	KTVD	2,297	87.4%	0.1%	0.2%	12.2%	0.1%
2010	WLBZ	1,907	79.4%	0.0%	11.2%	9.4%	0.1%
2010	WVII	1,907	83.1%	0.3%	13.4%	3.2%	0.1%
2010	WBOY	1,798	80.8%	0.3%	11.0%	8.0%	0.1%
2010	WDTV	1,798	79.5%	0.2%	11.7%	8.6%	0.1%
2010	WCAU	1,760	75.8%	0.1%	12.2%	11.8%	0.0%
2010	KCTV	1,698	75.4%	0.1%	11.6%	13.0%	0.1%
2010	WDAF	1,698	58.6%	0.0%	18.6%	22.7%	0.0%
2010	WCWJ	1,587	88.2%	4.4%	2.9%	4.4%	0.0%
2010	WJXX	1,587	74.1%	0.2%	15.3%	10.4%	0.0%
2010	WHAG	1,561	74.7%	0.9%	13.1%	11.3%	0.1%
2010	WLS	1,538	75.1%	0.1%	11.5%	13.3%	0.1%
2010	WBDT	1,524	94.2%	0.3%	1.5%	4.0%	0.0%
2010	WKEF	1,524	82.3%	0.0%	11.7%	6.0%	0.0%
2010	WWNY	1,296	82.4%	0.1%	10.5%	7.0%	0.0%
2010	KOLN	1,097	80.9%	0.0%	10.3%	8.8%	0.0%
2010	WFLD	1,060	61.6%	0.2%	20.5%	17.8%	0.0%
2010	WBBM	1,023	80.7%	0.0%	11.0%	8.2%	0.0%
2010	KARK	1,003	75.8%	0.3%	13.6%	10.2%	0.0%
2010	KHOU	970	78.9%	0.4%	10.0%	10.8%	0.0%
2010	WMAQ	928	77.5%	0.0%	11.7%	10.7%	0.0%
2010	KTBY	686	88.9%	0.7%	7.1%	3.4%	0.0%
2010	WEYI	605	82.0%	0.2%	12.0%	5.8%	0.0%
2010	WJRT	605	73.8%	0.1%	13.7%	12.5%	0.0%
2010	KOCO	499	66.9%	0.2%	25.6%	7.3%	0.0%
2010	WBNX	419	98.4%	1.5%	0.0%	0.1%	0.0%
2010	WPLG	366	77.0%	0.0%	12.2%	10.8%	0.0%
2010	WSEE	366	82.9%	0.1%	11.6%	5.3%	0.0%
2010	WTVJ	366	81.4%	0.0%	9.6%	9.1%	0.0%
2010	WBNG	334	73.9%	0.4%	16.3%	9.4%	0.0%
2010	WXIA	314	86.7%	0.2%	5.0%	8.1%	0.0%
2010	WGCL	299	62.3%	2.4%	27.3%	7.9%	0.0%
2010	WSB	283	76.9%	0.1%	7.6%	15.5%	0.0%
2010	WPTZ	141	78.7%	0.2%	14.2%	7.0%	0.0%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2010	KEVN	103	70.9%	0.2%	18.0%	10.9%	0.0%
2010	KOTA	103	81.5%	0.4%	13.0%	5.2%	0.0%
2011	WGNA	21,775,277	5.8%	1.9%	43.0%	49.2%	14.9%
2011	WPIX	1,539,134	73.1%	0.1%	5.4%	21.4%	9.4%
2011	WSFL	1,537,300	94.5%	0.1%	4.0%	1.4%	8.8%
2011	KTLA	516,833	66.1%	0.1%	1.1%	32.6%	3.9%
2011	XETV	515,466	75.5%	3.8%	0.0%	20.7%	3.6%
2011	WNYW	488,809	60.7%	0.2%	16.7%	22.3%	4.4%
2011	WABC	439,282	77.3%	0.0%	9.5%	13.1%	5.1%
2011	WCBS	429,333	74.8%	0.0%	13.5%	11.7%	4.7%
2011	WDCW	424,959	93.9%	0.7%	2.4%	3.1%	2.9%
2011	WNBC	410,683	77.6%	0.0%	10.4%	12.0%	4.7%
2011	KTTV	343,608	63.9%	0.1%	12.3%	23.7%	3.2%
2011	KABC	306,135	76.7%	0.0%	7.6%	15.7%	3.8%
2011	KCBS	299,831	77.2%	0.0%	10.8%	12.0%	3.5%
2011	KNBC	293,458	81.3%	0.0%	7.5%	11.2%	3.5%
2011	WSBK	156,691	89.1%	0.0%	4.6%	6.2%	1.1%
2011	KWGN	154,190	81.7%	0.2%	0.3%	17.8%	1.3%
2011	WWOR	153,659	79.6%	4.6%	9.6%	6.2%	1.3%
2011	WNUV	80,238	84.3%	2.7%	10.9%	2.0%	0.7%
2011	KGO	75,803	78.0%	0.0%	7.2%	14.8%	1.2%
2011	WLBT	62,602	77.0%	0.1%	9.7%	13.1%	1.0%
2011	KMAX	35,928	78.8%	0.0%	4.6%	16.6%	0.5%
2011	KXVO	35,055	92.7%	2.1%	2.6%	2.6%	0.4%
2011	KTVU	33,645	64.6%	0.1%	11.4%	23.9%	0.5%
2011	WTIC	30,533	60.4%	0.0%	17.2%	22.4%	0.5%
2011	WICS	29,814	82.4%	0.1%	6.2%	11.3%	0.5%
2011	KPIX	29,092	74.0%	0.0%	11.3%	14.7%	0.5%
2011	WTVY	26,655	77.2%	0.1%	12.5%	10.1%	0.5%
2011	KNTV	26,634	77.7%	0.0%	10.1%	12.3%	0.5%
2011	WRC	24,760	73.0%	0.0%	10.7%	16.3%	0.5%
2011	WUSA	24,760	74.0%	0.1%	13.1%	12.8%	0.5%
2011	WDSU	24,094	76.8%	0.1%	10.4%	12.8%	0.5%
2011	WWL	24,094	72.8%	0.0%	12.1%	15.1%	0.5%
2011	WNOL	19,986	97.3%	0.4%	2.1%	0.2%	0.3%
2011	WLFL	19,975	91.4%	1.0%	0.0%	7.7%	0.2%
2011	WJHG	19,485	79.2%	0.2%	10.0%	10.5%	0.4%
2011	WVLA	17,553	82.4%	0.2%	9.7%	7.8%	0.4%
2011	WGBC	17,463	81.5%	0.0%	16.6%	1.9%	0.3%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2011	WTOK	17,463	81.8%	0.3%	9.7%	8.3%	0.4%
2011	KSAT	15,847	76.8%	0.2%	10.1%	13.0%	0.3%
2011	WCAU	15,016	76.1%	0.1%	10.5%	13.3%	0.3%
2011	WMUR	14,856	74.7%	0.0%	11.3%	13.9%	0.3%
2011	WRTV	13,151	75.9%	0.1%	10.6%	13.4%	0.3%
2011	WTHR	13,151	78.3%	0.0%	9.7%	12.0%	0.3%
2011	WXIN	13,151	57.6%	0.0%	17.1%	25.3%	0.3%
2011	WHBQ	13,061	57.6%	0.2%	16.6%	25.7%	0.2%
2011	WMC	13,061	75.6%	0.1%	10.6%	13.7%	0.3%
2011	WREG	13,061	71.5%	0.1%	11.9%	16.5%	0.3%
2011	KSHB	12,751	77.3%	0.0%	10.4%	12.3%	0.3%
2011	WBDT	11,088	91.5%	0.2%	2.6%	5.8%	0.2%
2011	KFVS	9,770	80.6%	0.1%	12.7%	6.6%	0.2%
2011	WPSD	9,770	77.1%	0.2%	12.0%	10.8%	0.2%
2011	WCAX	9,396	75.8%	0.0%	13.0%	11.1%	0.2%
2011	WNNE	9,396	82.0%	0.1%	9.8%	8.2%	0.2%
2011	WVNY	9,396	81.4%	0.1%	11.5%	7.0%	0.2%
2011	WFFF	9,363	67.3%	0.3%	19.6%	12.8%	0.2%
2011	KEYT	9,155	84.8%	0.0%	4.0%	11.1%	0.2%
2011	KARE	9,035	75.0%	0.1%	10.6%	14.3%	0.2%
2011	KSTP	9,035	71.5%	0.0%	10.0%	18.4%	0.2%
2011	WBNX	9,013	99.4%	0.6%	0.0%	0.0%	0.1%
2011	WBNS	8,805	74.0%	0.0%	13.7%	12.2%	0.2%
2011	WSYX	8,805	77.4%	0.0%	12.2%	10.3%	0.2%
2011	WTTV	8,547	95.9%	0.1%	0.8%	3.2%	0.1%
2011	KBMT	7,640	78.9%	0.2%	11.2%	9.7%	0.2%
2011	KFDM	7,640	74.2%	2.6%	11.3%	11.8%	0.2%
2011	WTTE	7,492	67.2%	0.2%	19.3%	13.3%	0.2%
2011	WKTV	7,369	80.4%	0.1%	10.5%	9.0%	0.2%
2011	WKEF	6,370	85.9%	0.0%	7.0%	7.0%	0.2%
2011	KMSP	6,360	55.8%	0.1%	13.8%	30.3%	0.1%
2011	KCTV	6,163	73.0%	0.0%	12.5%	14.5%	0.2%
2011	WDAF	6,163	52.4%	0.0%	17.3%	30.3%	0.1%
2011	WLBZ	5,699	79.5%	0.0%	9.8%	10.6%	0.2%
2011	WVII	5,699	83.8%	0.1%	10.4%	5.7%	0.2%
2011	WBNG	5,600	76.6%	0.1%	13.5%	9.7%	0.1%
2011	WHAG	5,497	71.0%	2.7%	12.0%	14.2%	0.1%
2011	WDTV	5,068	76.7%	0.1%	13.4%	9.8%	0.1%
2011	WAPT	4,536	79.2%	0.2%	9.5%	11.2%	0.1%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2011	WJTV	4,536	76.2%	0.1%	13.6%	10.1%	0.1%
2011	KFXF	4,490	84.1%	0.3%	15.2%	0.5%	0.1%
2011	WGNO	4,266	71.5%	0.1%	17.0%	11.4%	0.1%
2011	KOLN	3,228	77.7%	0.0%	11.5%	10.8%	0.1%
2011	WJXX	2,840	81.6%	0.1%	5.7%	12.7%	0.1%
2011	KALB	2,626	75.0%	2.5%	15.1%	7.4%	0.1%
2011	KHOU	2,605	74.9%	0.1%	11.5%	13.6%	0.1%
2011	WBOY	2,361	82.4%	0.1%	8.6%	8.9%	0.1%
2011	WNAB	2,022	93.4%	0.6%	0.0%	6.0%	0.0%
2011	WSMV	2,022	68.0%	0.1%	15.3%	16.6%	0.1%
2011	WTVF	2,022	72.4%	0.1%	13.7%	13.8%	0.1%
2011	WEYI	1,824	82.2%	0.1%	10.7%	7.0%	0.1%
2011	WJRT	1,824	75.3%	0.0%	10.7%	14.0%	0.1%
2011	WHEC	1,822	75.0%	0.2%	15.3%	9.5%	0.1%
2011	WLMT	1,423	84.0%	0.6%	3.7%	11.8%	0.0%
2011	WWHO	1,313	95.3%	0.5%	4.1%	0.1%	0.0%
2011	WTVH	1,072	72.8%	0.0%	16.7%	10.4%	0.0%
2011	WPTZ	1,031	81.7%	0.1%	10.1%	8.1%	0.0%
2011	KHGI	923	69.2%	0.1%	17.7%	13.0%	0.0%
2011	KBSI	775	73.0%	2.8%	15.5%	8.7%	0.0%
2011	WCWJ	476	71.0%	3.9%	17.1%	8.0%	0.0%
2011	KEVN	316	71.0%	0.1%	16.1%	12.9%	0.0%
2011	KOTA	316	84.0%	0.2%	9.6%	6.2%	0.0%
2012	WGNA	21,502,212	6.3%	0.1%	40.6%	53.0%	12.9%
2012	WPIX	1,135,621	74.0%	0.1%	3.8%	22.1%	11.8%
2012	WDCW	524,947	92.9%	0.8%	4.8%	1.5%	5.2%
2012	WNYW	414,289	61.8%	0.2%	16.7%	21.2%	5.5%
2012	WCBS	391,139	76.1%	0.0%	12.2%	11.7%	5.7%
2012	WABC	371,811	75.8%	0.0%	8.6%	15.6%	5.3%
2012	WNBC	360,415	79.8%	0.0%	8.4%	11.8%	6.2%
2012	KTLA	310,197	66.0%	0.1%	0.7%	33.1%	3.6%
2012	KTTV	307,596	63.8%	0.2%	12.5%	23.5%	4.0%
2012	WSFL	282,364	92.1%	0.1%	2.5%	5.3%	3.2%
2012	KABC	266,527	75.3%	0.1%	7.1%	17.5%	3.9%
2012	KNBC	260,259	82.7%	0.0%	6.8%	10.5%	4.5%
2012	KCBS	256,064	77.9%	0.0%	10.0%	12.1%	3.8%
2012	WWOR	141,476	81.6%	5.1%	7.8%	5.5%	1.5%
2012	KWGN	134,921	83.3%	0.0%	0.0%	16.7%	1.5%
2012	WSBK	128,586	90.8%	0.0%	3.7%	5.5%	1.3%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2012	WPCW	48,268	77.3%	0.4%	6.2%	16.0%	0.6%
2012	WLBT	43,039	81.8%	0.1%	6.1%	12.0%	0.8%
2012	KXVO	42,796	94.2%	0.6%	1.3%	4.0%	0.5%
2012	WVLA	41,009	80.4%	0.2%	10.8%	8.6%	0.8%
2012	WLFL	32,647	92.4%	1.1%	0.0%	6.4%	0.4%
2012	KGO	29,814	74.2%	0.1%	7.4%	18.3%	0.5%
2012	KMAX	29,132	78.2%	0.0%	4.3%	17.5%	0.4%
2012	WRC	28,871	76.7%	0.0%	8.8%	14.5%	0.6%
2012	XETV	28,839	77.2%	4.1%	0.0%	18.8%	0.3%
2012	KSHB	27,967	78.9%	0.0%	8.5%	12.5%	0.6%
2012	WTVY	27,419	79.2%	0.1%	10.2%	10.5%	0.5%
2012	KTVU	27,292	64.1%	0.1%	11.3%	24.5%	0.5%
2012	WMC	24,814	77.5%	0.1%	9.3%	13.1%	0.5%
2012	WUSA	23,936	75.9%	0.0%	11.2%	12.9%	0.4%
2012	KPIX	23,715	74.9%	0.0%	10.9%	14.2%	0.4%
2012	WCAU	23,173	79.2%	0.0%	8.5%	12.3%	0.5%
2012	KNTV	21,823	79.2%	0.0%	9.5%	11.3%	0.5%
2012	WNOL	20,044	97.3%	0.4%	2.0%	0.4%	0.3%
2012	WJHG	19,944	80.9%	0.3%	8.8%	10.0%	0.4%
2012	KRNSCD	18,967	98.6%	0.6%	0.0%	0.9%	0.2%
2012	WMUR	18,444	75.2%	0.1%	11.0%	13.7%	0.3%
2012	WPSD	18,077	80.5%	0.1%	9.2%	10.1%	0.4%
2012	KSAT	16,961	73.0%	0.1%	9.1%	17.8%	0.3%
2012	WBDT	16,592	93.2%	0.1%	1.9%	4.7%	0.2%
2012	WHBQ	16,324	57.9%	0.2%	16.6%	25.4%	0.3%
2012	WREG	16,324	71.2%	0.1%	11.0%	17.8%	0.3%
2012	WRTV	15,223	75.9%	0.1%	9.5%	14.5%	0.3%
2012	WXIN	15,120	57.2%	0.0%	16.4%	26.4%	0.3%
2012	WTHR	14,696	80.8%	0.0%	8.2%	10.9%	0.3%
2012	WLMT	14,407	84.8%	0.6%	3.0%	11.6%	0.2%
2012	WDSU	14,300	80.4%	0.0%	7.0%	12.6%	0.3%
2012	WBNX	13,799	99.4%	0.5%	0.0%	0.0%	0.2%
2012	WSYX	13,521	78.2%	0.1%	10.0%	11.8%	0.2%
2012	KALB	13,242	82.0%	2.3%	8.5%	7.3%	0.3%
2012	KLAX	13,242	85.8%	0.0%	9.1%	5.1%	0.2%
2012	KCTV	12,222	73.2%	0.0%	11.4%	15.3%	0.2%
2012	WBNS	11,473	76.2%	0.0%	11.7%	12.0%	0.2%
2012	WCAX	10,420	77.2%	0.0%	11.9%	10.9%	0.2%
2012	WNNE	10,420	84.5%	0.1%	8.3%	7.1%	0.2%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2012	WVNY	10,420	80.0%	0.3%	10.3%	9.4%	0.2%
2012	WFFF	10,409	69.8%	0.3%	18.5%	11.5%	0.2%
2012	WTOK	10,178	82.0%	0.2%	8.6%	9.2%	0.2%
2012	WHEC	10,088	82.5%	0.1%	8.6%	8.8%	0.2%
2012	KARE	9,946	79.1%	0.1%	9.0%	11.9%	0.2%
2012	KSTP	9,946	71.2%	0.0%	9.0%	19.8%	0.2%
2012	KFVS	9,630	79.0%	0.0%	14.5%	6.5%	0.2%
2012	WTVH	9,331	77.4%	0.0%	13.0%	9.6%	0.2%
2012	WWL	9,311	67.8%	0.0%	17.8%	14.4%	0.2%
2012	WTTV	9,180	95.5%	0.0%	0.1%	4.4%	0.1%
2012	WKTV	9,129	83.3%	0.0%	8.7%	7.9%	0.2%
2012	WHAG	8,573	76.3%	2.5%	9.5%	11.7%	0.2%
2012	KATC	8,315	84.1%	0.1%	8.9%	6.9%	0.2%
2012	KLFY	8,315	83.7%	0.1%	10.0%	6.3%	0.2%
2012	WTTE	8,213	69.4%	0.2%	17.3%	13.1%	0.2%
2012	WGNO	7,539	82.0%	0.1%	6.2%	11.7%	0.1%
2012	WLBZ	7,327	82.2%	0.0%	8.2%	9.6%	0.2%
2012	WVII	7,327	86.1%	0.1%	9.2%	4.6%	0.1%
2012	WBNG	7,068	78.3%	0.1%	12.2%	9.5%	0.1%
2012	KBSI	7,002	73.2%	2.3%	17.0%	7.5%	0.1%
2012	WWHO	5,309	97.3%	0.4%	1.6%	0.8%	0.1%
2012	WDAF	4,788	61.7%	0.0%	5.9%	32.4%	0.1%
2012	KFXF	4,725	85.7%	0.2%	13.5%	0.6%	0.1%
2012	WAPT	4,564	78.8%	0.2%	8.5%	12.6%	0.1%
2012	WJTV	4,564	77.1%	0.1%	12.6%	10.2%	0.1%
2012	WDTV	3,956	80.2%	0.0%	10.7%	9.1%	0.1%
2012	KOLN	3,949	77.4%	0.0%	10.8%	11.8%	0.1%
2012	WNAB	3,905	96.3%	0.6%	0.0%	3.1%	0.1%
2012	WSMV	3,905	75.2%	0.1%	6.7%	18.0%	0.1%
2012	KHGI	3,620	77.2%	0.1%	9.4%	13.4%	0.1%
2012	WGBC	3,322	86.9%	0.0%	13.0%	0.2%	0.1%
2012	WCHS	3,079	80.0%	0.2%	11.3%	8.5%	0.1%
2012	WBOY	2,955	83.7%	0.1%	7.6%	8.6%	0.1%
2012	WEYI	2,479	85.4%	0.1%	8.8%	5.7%	0.1%
2012	WJRT	2,479	75.5%	0.0%	9.4%	15.1%	0.1%
2012	WPTZ	2,083	84.4%	0.1%	8.4%	7.2%	0.1%
2012	KTMF	1,823	81.1%	1.4%	15.1%	2.4%	0.0%
2012	WTIC	820	60.2%	0.0%	18.0%	21.8%	0.0%
2012	KBMT	724	83.8%	0.2%	5.3%	10.7%	0.0%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2012	KFDM	724	70.5%	3.4%	14.0%	12.1%	0.0%
2012	KEYC	664	79.4%	0.3%	11.3%	9.0%	0.0%
2012	WISE	527	80.0%	0.1%	15.4%	4.6%	0.0%
2012	KEVN	413	71.4%	0.1%	15.7%	12.8%	0.0%
2012	KOTA	413	84.8%	0.2%	8.7%	6.3%	0.0%
2012	WNKY	249	82.1%	0.9%	15.6%	1.4%	0.0%
2013	WGNA	20,403,180	6.0%	0.0%	39.7%	54.3%	11.7%
2013	WPIX	1,094,274	75.9%	0.1%	3.8%	20.3%	13.8%
2013	WDCW	637,235	95.7%	0.2%	3.0%	1.1%	7.3%
2013	WNYW	371,656	63.9%	0.1%	14.1%	21.9%	5.3%
2013	WCBS	357,865	77.5%	0.0%	11.2%	11.2%	6.2%
2013	WABC	347,281	77.0%	0.1%	7.9%	15.0%	6.1%
2013	WNBC	331,297	79.4%	0.0%	8.0%	12.6%	6.1%
2013	KTTV	265,454	70.5%	0.1%	11.0%	18.4%	3.9%
2013	KTLA	247,423	68.9%	0.1%	1.0%	30.0%	3.4%
2013	KABC	238,642	75.6%	0.1%	6.7%	17.6%	4.2%
2013	KCBS	225,956	78.1%	0.0%	9.8%	12.1%	4.0%
2013	KNBC	220,440	81.2%	0.0%	6.7%	12.1%	4.1%
2013	WWOR	120,971	82.9%	4.7%	6.3%	6.1%	1.4%
2013	KWGN	117,095	84.1%	0.0%	0.0%	15.9%	1.5%
2013	WSFL	115,638	96.7%	0.0%	2.9%	0.4%	1.5%
2013	WSBK	111,312	91.2%	0.0%	3.6%	5.2%	1.2%
2013	WVLA	81,896	83.5%	0.1%	7.8%	8.6%	1.6%
2013	WPCW	50,578	81.3%	2.6%	1.2%	14.9%	0.7%
2013	KXVO	48,622	95.8%	0.1%	1.2%	2.9%	0.7%
2013	WMC	33,420	77.5%	0.0%	8.4%	14.0%	0.7%
2013	WRC	30,966	75.4%	0.0%	8.2%	16.3%	0.7%
2013	WCAU	27,385	77.5%	0.0%	7.8%	14.7%	0.6%
2013	WLFL	26,075	93.6%	0.5%	0.1%	5.8%	0.4%
2013	WMUR	25,823	79.3%	0.1%	9.0%	11.6%	0.5%
2013	KGO	24,276	76.5%	0.1%	6.8%	16.7%	0.5%
2013	KMAX	23,844	79.8%	0.0%	3.0%	17.2%	0.4%
2013	KSHB	23,665	76.8%	0.0%	8.3%	14.8%	0.5%
2013	WNOL	23,225	95.9%	0.1%	2.1%	1.9%	0.3%
2013	KTVU	22,586	65.1%	0.1%	10.4%	24.4%	0.4%
2013	WLMT	21,377	86.2%	0.2%	4.2%	9.4%	0.3%
2013	WPSD	20,866	81.9%	0.1%	7.7%	10.3%	0.4%
2013	KPIX	20,123	76.8%	0.0%	9.9%	13.3%	0.4%
2013	WBDT	18,822	86.5%	0.0%	2.0%	11.4%	0.3%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2013	KNTV	18,553	79.6%	0.0%	8.6%	11.8%	0.4%
2013	KRNSCD	17,332	98.8%	0.5%	0.0%	0.7%	0.2%
2013	KSAT	17,249	73.5%	0.1%	8.7%	17.7%	0.3%
2013	WHBQ	16,973	61.0%	0.1%	13.6%	25.3%	0.3%
2013	WREG	16,973	73.4%	0.1%	10.4%	16.1%	0.3%
2013	WBNX	16,747	99.7%	0.3%	0.0%	0.1%	0.2%
2013	KALB	16,401	87.4%	0.1%	10.0%	2.6%	0.3%
2013	KLAX	16,401	86.7%	0.1%	8.3%	4.9%	0.3%
2013	WRTV	16,298	77.0%	0.1%	9.2%	13.7%	0.3%
2013	WTHR	16,298	80.4%	0.0%	7.8%	11.8%	0.4%
2013	WXIN	16,298	60.0%	0.0%	13.6%	26.4%	0.3%
2013	WSYX	14,794	78.9%	0.1%	8.9%	12.1%	0.3%
2013	WTVH	14,455	79.2%	0.0%	12.1%	8.7%	0.3%
2013	KCTV	13,973	75.0%	0.0%	10.5%	14.5%	0.3%
2013	WHEC	12,932	81.5%	0.0%	8.0%	10.4%	0.3%
2013	WCAX	10,493	78.3%	0.0%	11.1%	10.6%	0.2%
2013	WFFF	10,493	71.4%	0.1%	16.1%	12.4%	0.2%
2013	WNNE	10,493	84.5%	0.0%	7.6%	7.9%	0.2%
2013	WVNY	10,493	82.5%	0.4%	8.6%	8.4%	0.2%
2013	KARE	10,426	79.4%	0.1%	8.1%	12.5%	0.2%
2013	KSTP	10,426	72.0%	0.1%	8.3%	19.6%	0.2%
2013	WHAG	10,273	75.0%	3.7%	8.7%	12.5%	0.2%
2013	WKTV	9,711	83.2%	0.0%	8.0%	8.8%	0.2%
2013	WTTV	9,565	98.3%	0.0%	0.0%	1.7%	0.1%
2013	KATC	9,235	85.7%	0.1%	7.6%	6.6%	0.2%
2013	KLFY	9,235	84.2%	0.2%	9.7%	6.0%	0.2%
2013	KBSI	9,023	77.0%	2.8%	14.0%	6.3%	0.2%
2013	KFVS	9,023	82.7%	0.0%	10.8%	6.4%	0.2%
2013	WBNS	8,743	77.8%	0.0%	10.5%	11.7%	0.2%
2013	WTTE	8,743	71.0%	0.1%	14.3%	14.6%	0.2%
2013	WJHG	8,380	85.4%	0.1%	4.0%	10.5%	0.2%
2013	WLBZ	8,087	82.3%	0.0%	7.6%	10.1%	0.2%
2013	WVII	8,087	85.5%	0.1%	8.4%	6.0%	0.2%
2013	WCHS	6,533	83.0%	0.1%	8.5%	8.4%	0.1%
2013	WWHO	6,050	97.5%	0.1%	1.4%	0.9%	0.1%
2013	WUSA	5,315	74.4%	0.0%	12.9%	12.7%	0.1%
2013	WBNG	5,134	80.8%	0.0%	9.5%	9.7%	0.1%
2013	WAPT	4,553	80.8%	0.1%	7.8%	11.3%	0.1%
2013	WJTV	4,553	78.2%	0.1%	11.9%	9.8%	0.1%

Year	Call sign	Avg. monthly subscribers	Share PS	Share DEV	Share JSC	Share CTV	Share of total viewing
2013	WLBT	4,553	79.6%	0.1%	8.0%	12.3%	0.1%
2013	WEYI	2,934	85.8%	0.0%	8.3%	5.9%	0.1%
2013	KOLN	2,647	79.6%	0.0%	8.5%	11.9%	0.1%
2013	WPTZ	2,182	84.5%	0.0%	7.6%	7.9%	0.1%
2013	KHGI	1,659	82.3%	0.1%	4.8%	12.8%	0.0%
2013	WJRT	1,656	79.1%	0.1%	6.0%	14.8%	0.0%
2013	KEYC	715	79.9%	0.1%	10.2%	9.8%	0.0%
2013	KEVN	460	74.4%	0.0%	13.7%	11.9%	0.0%
2013	KOTA	460	86.0%	0.1%	7.6%	6.3%	0.0%
2013	KFXF	279	87.3%	0.1%	12.0%	0.6%	0.0%

Appendix F. Distant viewership (Nielsen) versus predicted viewing

Figure 39: Distant viewership (Nielsen) versus predicted (Gray Model 1) viewing—2011

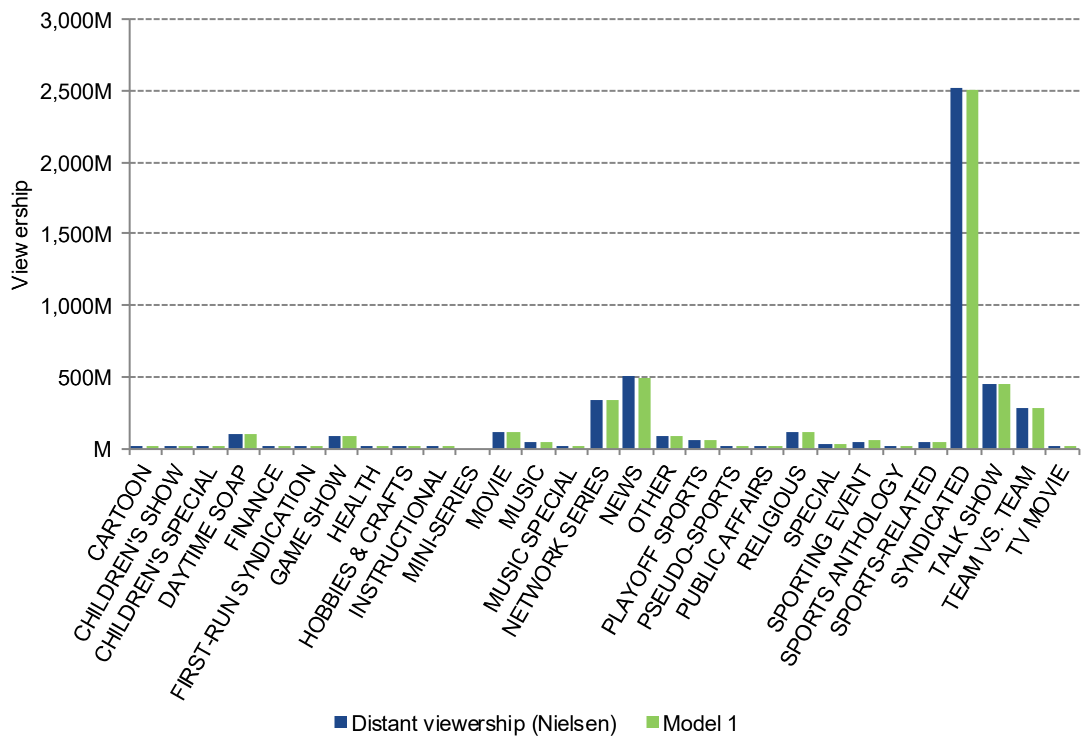


Figure 40: Distant viewership (Nielsen) versus predicted (Gray Model 1) viewing—2012

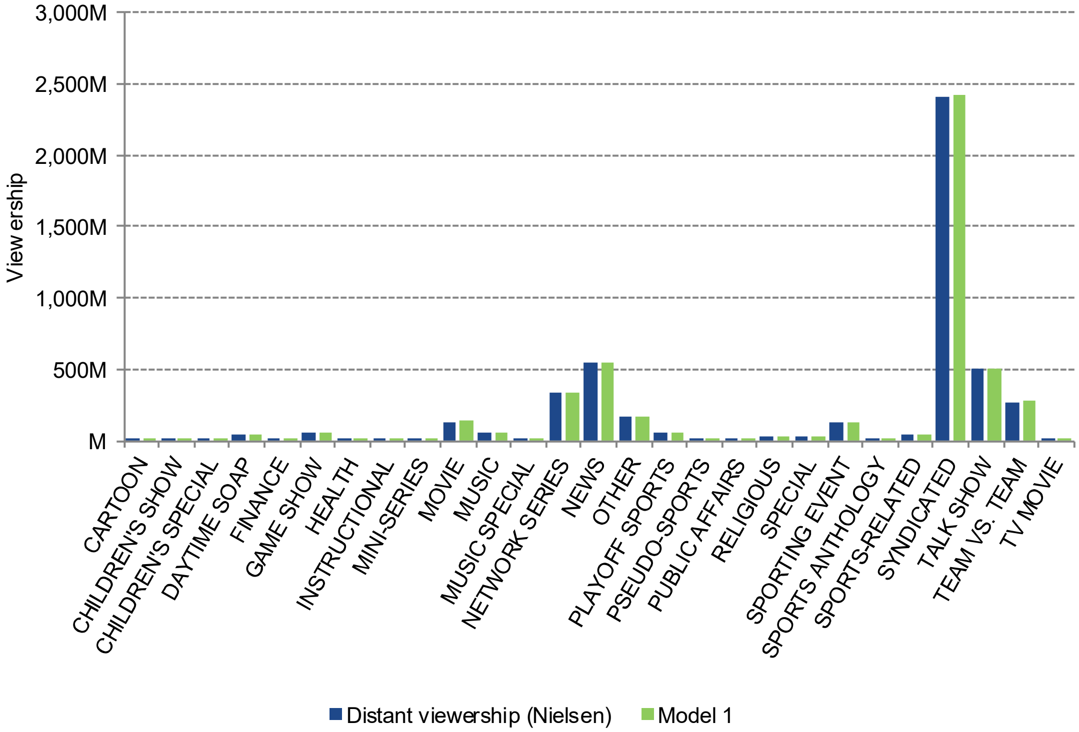
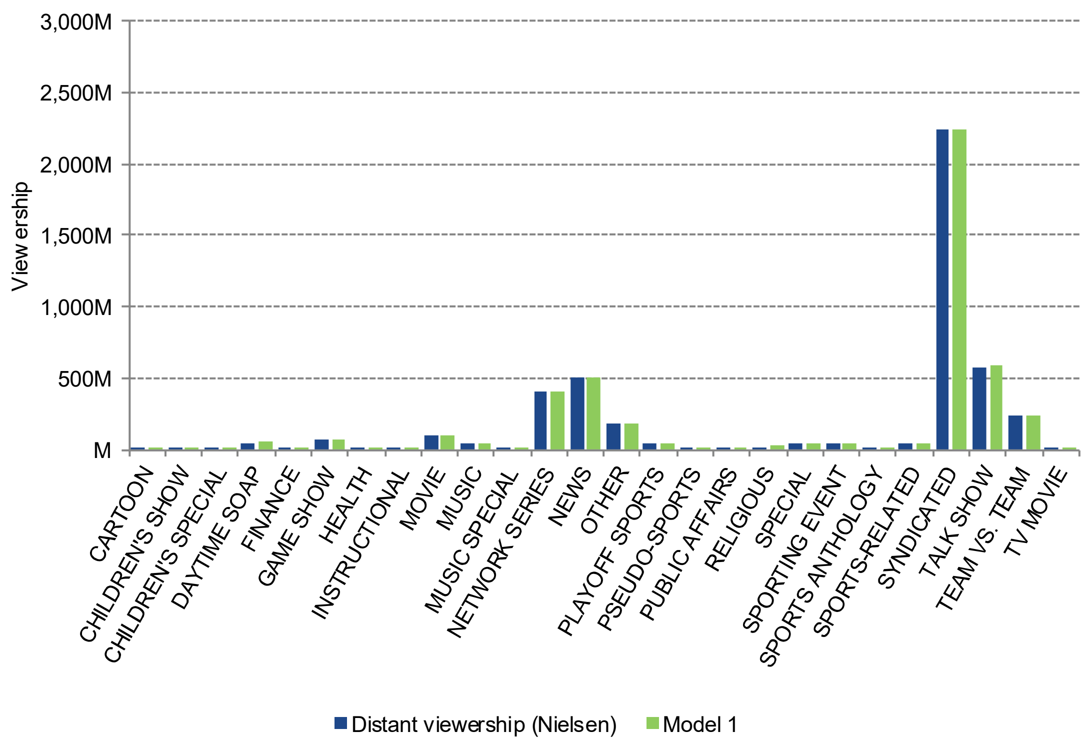


Figure 41: Distant viewership (Nielsen) versus predicted (Gray Model 1) viewing—2013



Appendix G. Satellite Subscribers

Figure 42: Comparison of DMA ranking by satellite penetration rate and number of satellite subscribers – 2011

DMA	Penetration rate	Average annual households	Satellite subscribers		
			Total	Percentage	Cumulative
COLUMBUS-TUPELO-WEST POINT	61.0%	190,270	116,065	0.3%	0.3%
SHREVEPORT-TEXARKANA	57.0%	387,060	220,624	0.6%	1.0%
PADUCAH-CAPE GIRARDEAU-HARRISBG-MT VERNON	55.0%	398,820	219,351	0.6%	1.6%
CHICO-REDDING	55.0%	198,370	109,104	0.3%	1.9%
MERIDIAN	55.0%	72,280	39,754	0.1%	2.0%
TYLER-LONGVIEW (LUFKIN & NACOGDOCHES)	54.0%	269,760	145,670	0.4%	2.4%
ABILENE-SWEETWATER	54.0%	115,200	62,208	0.2%	2.6%
JACKSON, MISS.	53.0%	338,030	179,156	0.5%	3.1%
COLUMBIA - JEFFERSON CITY	52.0%	405,670	210,948	0.6%	3.7%
WICHITA FALLS & LAWTON	52.0%	157,030	81,656	0.2%	3.9%
TERRE HAUTE	52.0%	144,950	75,374	0.2%	4.2%
SPRINGFIELD, MO.	51.0%	424,270	216,378	0.6%	4.8%
MONROE-EL DORADO	51.0%	177,900	90,729	0.3%	5.0%
SHERMAN-ADA	51.0%	129,480	66,035	0.2%	5.2%
LITTLE ROCK-PINE BLUFF	50.0%	573,670	286,835	0.8%	6.0%
ROANOKE-LYNCHBURG	50.0%	464,480	232,240	0.7%	6.7%
MEDFORD-KLAMATH FALLS	50.0%	172,230	86,115	0.2%	6.9%
IDAHO FALLS-POCATELLO	50.0%	128,860	64,430	0.2%	7.1%
AMARILLO	48.0%	195,070	93,634	0.3%	7.4%
MISSOULA	48.0%	113,380	54,422	0.2%	7.6%
TWIN FALLS	48.0%	65,310	31,349	0.1%	7.6%
GREENVILLE-SPARTANBURG-ASHEVILLE-ANDRSN	47.0%	878,550	412,919	1.2%	8.8%
FRESNO-VISALIA	47.0%	581,340	273,230	0.8%	9.6%
BOISE	47.0%	262,920	123,572	0.4%	10.0%
YAKIMA-PASCO-RICHLAND-KENNEWICK	47.0%	225,320	105,900	0.3%	10.3%
JOPLIN-PITTSBURG	47.0%	156,360	73,489	0.2%	10.5%
YUMA-EL CENTRO	47.0%	118,700	55,789	0.2%	10.6%
BIRMINGHAM	46.0%	747,190	343,707	1.0%	11.6%
ALBUQUERQUE-SANTA FE	46.0%	703,720	323,711	0.9%	12.5%
MACON	46.0%	241,120	110,915	0.3%	12.8%
QUINCY-HANNIBAL-KEOKUK	46.0%	102,010	46,925	0.1%	13.0%
SPOKANE	45.0%	424,220	190,899	0.5%	13.5%
RENO	45.0%	271,380	122,121	0.3%	13.9%
DULUTH-SUPERIOR	45.0%	174,570	78,557	0.2%	14.1%
ALBANY, GA.	45.0%	156,910	70,610	0.2%	14.3%
BANGOR	45.0%	144,130	64,859	0.2%	14.5%
CLARKSBURG-WESTON	45.0%	110,440	49,698	0.1%	14.6%
LEXINGTON	44.0%	515,320	226,741	0.6%	15.3%

DMA	Penetration rate	Average annual households	Satellite subscribers		
			Total	Percentage	Cumulative
COLORADO SPRINGS-PUEBLO	44.0%	336,880	148,227	0.4%	15.7%
BEAUMONT-PORT ARTHUR	44.0%	170,010	74,804	0.2%	15.9%
HATTIESBURG-LAUREL	44.0%	112,120	49,333	0.1%	16.0%
CHARLESTON-HUNTINGTON	42.0%	505,200	212,184	0.6%	16.6%
TRAVERSE CITY-CADILLAC	42.0%	242,700	101,934	0.3%	16.9%
PHOENIX	41.0%	1,881,310	771,337	2.2%	19.1%
DENVER	41.0%	1,572,740	644,823	1.8%	21.0%
SACRAMENTO-STOCKTON-MODESTO	41.0%	1,409,400	577,854	1.6%	22.6%
MEMPHIS	41.0%	693,860	284,483	0.8%	23.4%
TUCSON (NOGALES)	41.0%	461,450	189,195	0.5%	24.0%
MONTEREY-SALINAS	41.0%	229,150	93,952	0.3%	24.2%
GREAT FALLS	41.0%	65,900	27,019	0.1%	24.3%
SAINT LOUIS	40.0%	1,258,580	503,432	1.4%	25.7%
SALT LAKE CITY	40.0%	953,950	381,580	1.1%	26.8%
MOBILE-PENSACOLA	40.0%	539,190	215,676	0.6%	27.4%
BURLINGTON-PLATTSBURGH	40.0%	330,730	132,292	0.4%	27.8%
EVANSVILLE	40.0%	292,440	116,976	0.3%	28.2%
LINCOLN & HASTINGS-KEARNEY, PLUS	40.0%	279,820	111,928	0.3%	28.5%
COLUMBIA, S.C.	40.0%	178,610	71,444	0.2%	28.7%
LUBBOCK	40.0%	161,450	64,580	0.2%	28.9%
DOTHAN	40.0%	110,080	44,032	0.1%	29.0%
ALEXANDRIA, LA.	40.0%	90,640	36,256	0.1%	29.1%
BUTTE-BOZEMAN	40.0%	65,780	26,312	0.1%	29.2%
OTTUMWA-KIRKSVILLE	40.0%	51,370	20,548	0.1%	29.2%
TULSA	39.0%	535,820	208,970	0.6%	29.8%
TRI-CITIES, TENN.-VA.	39.0%	337,610	131,668	0.4%	30.2%
SOUTH BEND-ELKHART	39.0%	336,220	131,126	0.4%	30.6%
FORT SMITH	39.0%	304,060	118,583	0.3%	30.9%
GREENVILLE-NEW BERN-WASHINGTON	39.0%	294,550	114,875	0.3%	31.2%
WAUSAU-RHINELANDER	39.0%	186,010	72,544	0.2%	31.4%
ATLANTA	38.0%	2,047,080	777,890	2.2%	33.7%
DES MOINES-AMES	38.0%	432,820	164,472	0.5%	34.1%
WACO-TEMPLE-BRYAN	38.0%	344,020	130,728	0.4%	34.5%
SAVANNAH	38.0%	329,460	125,195	0.4%	34.9%
JOHNSTOWN-ALTOONA	38.0%	293,940	111,697	0.3%	35.2%
TALLAHASSEE-THOMASVILLE	38.0%	282,110	107,202	0.3%	35.5%
SAN ANGELO	38.0%	55,280	21,006	0.1%	35.5%
LOS ANGELES	37.0%	5,666,900	2,096,753	6.0%	41.5%
CHARLOTTE	37.0%	1,166,180	431,487	1.2%	42.7%
RALEIGH-DURHAM	37.0%	1,131,310	418,585	1.2%	43.9%
HUNTSVILLE-DECATUR, FLORENCE	37.0%	399,440	147,793	0.4%	44.4%
PRESQUE ISLE	37.0%	30,380	11,241	0.0%	44.4%
NASHVILLE	36.0%	1,039,430	374,195	1.1%	45.5%
NEW ORLEANS	36.0%	635,860	228,910	0.7%	46.1%
AUGUSTA	36.0%	257,030	92,531	0.3%	46.4%

DMA	Penetration rate	Average annual households	Satellite subscribers		
			Total	Percentage	Cumulative
EUGENE	36.0%	243,870	87,793	0.3%	46.6%
FARGO-VALLEY CITY	36.0%	241,990	87,116	0.2%	46.9%
SANTA BARBARA-SANTA MARIA-SAN LUIS OBISPO	36.0%	239,250	86,130	0.2%	47.1%
BAKERSFIELD	36.0%	225,670	81,241	0.2%	47.3%
ODESSA-MIDLAND	36.0%	146,310	52,672	0.2%	47.5%
CHARLOTTESVILLE	36.0%	76,700	27,612	0.1%	47.6%
GREENWOOD-GREENVILLE, MS	36.0%	69,450	25,002	0.1%	47.6%
DALLAS-FT. WORTH	35.0%	2,594,630	908,121	2.6%	50.2%
GREENSBORO-HIGH POINT-WINSTON-SALEM	35.0%	699,040	244,664	0.7%	50.9%
JACKSONVILLE	35.0%	678,430	237,451	0.7%	51.6%
KNOXVILLE	35.0%	557,040	194,964	0.6%	52.2%
CHAMPAIGN & SPRINGFIELD-DECATUR	35.0%	384,990	134,747	0.4%	52.5%
LANSING	35.0%	253,380	88,683	0.3%	52.8%
LAFAYETTE, LA.	35.0%	231,560	81,046	0.2%	53.0%
CORPUS CHRISTI	35.0%	199,370	69,780	0.2%	53.2%
BLUEFIELD-BECKLEY-OAK HILL	35.0%	143,280	50,148	0.1%	53.4%
BILLINGS	35.0%	109,090	38,182	0.1%	53.5%
RICHMOND-PETERSBURG	34.0%	558,500	189,890	0.5%	54.0%
CHATTANOOGA	34.0%	376,910	128,149	0.4%	54.4%
DAVENPORT-ROCK ISLAND-MOLINE	34.0%	309,800	105,332	0.3%	54.7%
FORT WAYNE	34.0%	277,050	94,197	0.3%	55.0%
SIOUX CITY	34.0%	155,490	52,867	0.2%	55.1%
GAINESVILLE	34.0%	130,460	44,356	0.1%	55.2%
JONESBORO	34.0%	83,000	28,220	0.1%	55.3%
JACKSON, TENN.	34.0%	77,700	26,418	0.1%	55.4%
FORT MYERS-NAPLES	33.0%	499,410	164,805	0.5%	55.9%
MADISON	33.0%	382,700	126,291	0.4%	56.2%
HARLINGEN-WESLACO-BROWNSVILLE-MCALLEN	33.0%	356,010	117,483	0.3%	56.6%
MONTGOMERY	33.0%	244,470	80,675	0.2%	56.8%
ERIE	33.0%	158,000	52,140	0.1%	56.9%
HARRISONBURG	33.0%	94,670	31,241	0.1%	57.0%
VICTORIA	33.0%	31,660	10,448	0.0%	57.1%
LAS VEGAS	32.0%	718,030	229,770	0.7%	57.7%
WILKES-BARRE-SCRANTON	32.0%	595,480	190,554	0.5%	58.3%
EL PASO	32.0%	315,130	100,842	0.3%	58.5%
PEORIA-BLOOMINGTON	32.0%	251,880	80,602	0.2%	58.8%
LA CROSSE-EAU CLAIRE	32.0%	216,510	69,283	0.2%	59.0%
MINOT-BISMARCK-DICKINSON (WILLISTON)	32.0%	138,730	44,394	0.1%	59.1%
GRAND JUNCTION-MONTROSE	32.0%	76,320	24,422	0.1%	59.2%
CASPER-RIVERTON	32.0%	56,700	18,144	0.1%	59.2%
SAINT JOSEPH	32.0%	48,040	15,373	0.0%	59.3%
ALPENA	32.0%	17,040	5,453	0.0%	59.3%
PORTLAND, ORE.	31.0%	1,197,780	371,312	1.1%	60.3%

DMA	Penetration rate	Average annual households	Satellite subscribers		
			Total	Percentage	Cumulative
SAN ANTONIO	31.0%	844,910	261,922	0.7%	61.1%
GRAND RAPIDS-KALAMAZOO-BATTLE CREEK	31.0%	740,230	229,471	0.7%	61.7%
OKLAHOMA CITY	31.0%	704,670	218,448	0.6%	62.4%
CEDAR RAPIDS-WATERLOO & DUBUQUE	31.0%	346,010	107,263	0.3%	62.7%
WILMINGTON	31.0%	191,630	59,405	0.2%	62.8%
ROCKFORD	31.0%	187,970	58,271	0.2%	63.0%
TOPEKA	31.0%	179,510	55,648	0.2%	63.2%
ROCHESTER-MASON CITY-AUSTIN	31.0%	144,590	44,823	0.1%	63.3%
LAKE CHARLES	31.0%	96,210	29,825	0.1%	63.4%
CHEYENNE-SCOTTSBLUFF-STERLING	31.0%	55,210	17,115	0.0%	63.4%
BUFFALO	30.0%	636,320	190,896	0.5%	64.0%
FLINT-SAGINAW-BAY CITY	30.0%	455,840	136,752	0.4%	64.3%
GREEN BAY-APPLETON	30.0%	445,510	133,653	0.4%	64.7%
COLUMBUS, GA.	30.0%	219,450	65,835	0.2%	64.9%
PANAMA CITY	30.0%	139,700	41,910	0.1%	65.0%
LAREDO	30.0%	70,090	21,027	0.1%	65.1%
HELENA	30.0%	28,030	8,409	0.0%	65.1%
NORTH PLATTE	30.0%	15,350	4,605	0.0%	65.1%
CHICAGO	29.0%	3,502,610	1,015,757	2.9%	68.0%
SAN FRANCISCO-OAKLAND-SAN JOSE	29.0%	2,523,520	731,821	2.1%	70.1%
HOUSTON	29.0%	2,177,220	631,394	1.8%	71.9%
CINCINNATI	29.0%	923,830	267,911	0.8%	72.7%
LOUISVILLE	29.0%	674,940	195,733	0.6%	73.2%
CHARLESTON, S.C.	29.0%	312,770	90,703	0.3%	73.5%
MARQUETTE	29.0%	87,670	25,424	0.1%	73.6%
MINNEAPOLIS-ST. PAUL	28.0%	1,753,780	491,058	1.4%	75.0%
INDIANAPOLIS	28.0%	1,106,420	309,798	0.9%	75.8%
WICHITA1-HUTCHINSON, PLUS	28.0%	457,880	128,206	0.4%	76.2%
BILOXI-GULFPORT	28.0%	126,610	35,451	0.1%	76.3%
RAPID CITY	28.0%	97,930	27,420	0.1%	76.4%
EUREKA	28.0%	61,570	17,240	0.0%	76.4%
ORLANDO-DAYTONA BEACH-MELBOURNE	27.0%	1,453,120	392,342	1.1%	77.6%
AUSTIN, TEX.	27.0%	707,430	191,006	0.5%	78.1%
SIOUX FALLS (MITCHELL)	27.0%	263,790	71,223	0.2%	78.3%
LAFAYETTE, IND.	27.0%	67,560	18,241	0.1%	78.4%
GLENDIVE	27.0%	4,040	1,091	0.0%	78.4%
MIAMI-FT. LAUDERDALE	26.0%	1,580,580	410,951	1.2%	79.5%
KANSAS CITY	26.0%	974,820	253,453	0.7%	80.3%
WEST PALM BEACH-FT. PIERCE	26.0%	773,890	201,211	0.6%	80.8%
FLORENCE-MYRTLE BEACH	26.0%	289,570	75,288	0.2%	81.0%
YOUNGSTOWN	26.0%	268,150	69,719	0.2%	81.2%
ELMIRA	26.0%	96,390	25,061	0.1%	81.3%
MANKATO	26.0%	52,640	13,686	0.0%	81.4%

DMA	Penetration rate	Average annual households	Satellite subscribers		
			Total	Percentage	Cumulative
CLEVELAND	25.0%	1,526,200	381,550	1.1%	82.4%
HARRISBURG-LANCASTER-LEBANON-YORK	25.0%	749,020	187,255	0.5%	83.0%
DAYTON	25.0%	527,030	131,758	0.4%	83.3%
TOLEDO	25.0%	445,600	111,400	0.3%	83.7%
BATON ROUGE	25.0%	334,730	83,683	0.2%	83.9%
WHEELING-STEUBENVILLE	25.0%	132,910	33,228	0.1%	84.0%
WATERTOWN	25.0%	95,750	23,938	0.1%	84.1%
ZANESVILLE	25.0%	32,550	8,138	0.0%	84.1%
WASHINGTON, D.C.	24.0%	2,389,710	573,530	1.6%	85.7%
PITTSBURGH	24.0%	1,160,820	278,597	0.8%	86.5%
NORFOLK-PORTSMOUTH-NEWPORT NEWS	24.0%	716,050	171,852	0.5%	87.0%
BEND	24.0%	66,680	16,003	0.0%	87.1%
PORTLAND-AUBURN	23.0%	410,300	94,369	0.3%	87.3%
PALM SPRINGS	23.0%	157,180	36,151	0.1%	87.4%
PARKERSBURG	23.0%	64,370	14,805	0.0%	87.5%
DETROIT	22.0%	1,883,840	414,445	1.2%	88.6%
COLUMBUS, OHIO	22.0%	915,950	201,509	0.6%	89.2%
ANCHORAGE	22.0%	154,820	34,060	0.1%	89.3%
SEATTLE-TACOMA	21.0%	1,874,750	393,698	1.1%	90.4%
BALTIMORE	21.0%	1,108,360	232,756	0.7%	91.1%
OMAHA	21.0%	418,290	87,841	0.3%	91.4%
BOWLING GREEN	21.0%	81,750	17,168	0.0%	91.4%
LIMA	21.0%	40,020	8,404	0.0%	91.4%
SALISBURY	20.0%	159,630	31,926	0.1%	91.5%
BINGHAMTON	20.0%	136,740	27,348	0.1%	91.6%
MILWAUKEE	19.0%	901,100	171,209	0.5%	92.1%
ROCHESTER, N.Y.	19.0%	392,090	74,497	0.2%	92.3%
ALBANY-SCHENECTADY-TROY	17.0%	557,860	94,836	0.3%	92.6%
UTICA	17.0%	104,990	17,848	0.1%	92.6%
PHILADELPHIA	16.0%	3,015,820	482,531	1.4%	94.0%
HARTFORD & NEW HAVEN	16.0%	1,018,770	163,003	0.5%	94.5%
SYRACUSE	16.0%	389,970	62,395	0.2%	94.6%
SAN DIEGO	15.0%	1,089,010	163,352	0.5%	95.1%
SPRINGFIELD-HOLYOKE	15.0%	269,500	40,425	0.1%	95.2%
NEW YORK	14.0%	7,515,330	1,052,146	3.0%	98.2%
TAMPA-ST. PETERSBURG, SARASOTA	14.0%	1,795,200	251,328	0.7%	98.9%
BOSTON	13.0%	2,460,290	319,838	0.9%	99.8%
PROVIDENCE-NEW BEDFORD	9.0%	620,600	55,854	0.2%	100.0%

Figure 43: Comparison of DMA ranking by satellite penetration rate and number of satellite subscribers – 2012

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
SHREVEPORT-TEXARKANA	59.0%	386,150	227,829	0.7%	0.7%
SPRINGFIELD, MO.	57.0%	423,010	241,116	0.7%	1.3%
PADUCAH-CAPE GIRARDEAU-HARRISBG-MT VERNON	57.0%	393,330	224,198	0.6%	2.0%
COLUMBUS-TUPELO-WEST POINT	56.0%	189,910	106,350	0.3%	2.3%
COLUMBIA - JEFFERSON CITY	56.0%	176,470	98,823	0.3%	2.6%
MERIDIAN	56.0%	70,190	39,306	0.1%	2.7%
CHICO-REDDING	55.0%	194,590	107,025	0.3%	3.0%
ABILENE-SWEETWATER	54.0%	115,630	62,440	0.2%	3.2%
SHERMAN-ADA	53.0%	128,790	68,259	0.2%	3.4%
ROANOKE-LYNCHBURG	52.0%	455,860	237,047	0.7%	4.0%
JACKSON, MISS.	52.0%	334,530	173,956	0.5%	4.5%
TYLER-LONGVIEW (LUFKIN & NACOGDOCHES)	52.0%	271,400	141,128	0.4%	4.9%
WICHITA FALLS & LAWTON	52.0%	160,540	83,481	0.2%	5.2%
LITTLE ROCK-PINE BLUFF	51.0%	571,630	291,531	0.8%	6.0%
MEDFORD-KLAMATH FALLS	51.0%	170,670	87,042	0.2%	6.3%
TERRE HAUTE	50.0%	142,780	71,390	0.2%	6.5%
MISSOULA	50.0%	114,590	57,295	0.2%	6.6%
QUINCY-HANNIBAL-KEOKUK	50.0%	104,790	52,395	0.1%	6.8%
TWIN FALLS	50.0%	65,800	32,900	0.1%	6.9%
FRESNO-VISALIA	49.0%	574,800	281,652	0.8%	7.7%
SPOKANE	49.0%	426,690	209,078	0.6%	8.3%
BOISE	49.0%	261,810	128,287	0.4%	8.6%
MONROE-EL DORADO	49.0%	177,410	86,931	0.2%	8.9%
IDAHO FALLS-POCATELLO	49.0%	128,940	63,181	0.2%	9.1%
GREENVILLE-SPARTANBURG-ASHEVILLE-ANDRSN	48.0%	860,930	413,246	1.2%	10.3%
COLORADO SPRINGS-PUEBLO	48.0%	343,160	164,717	0.5%	10.7%
JOPLIN-PITTSBURG	48.0%	153,910	73,877	0.2%	10.9%
BANGOR	48.0%	141,580	67,958	0.2%	11.1%
ALBUQUERQUE-SANTA FE	47.0%	710,050	333,724	1.0%	12.1%
YAKIMA-PASCO-RICHLAND-KENNEWICK	47.0%	230,010	108,105	0.3%	12.4%
AMARILLO	47.0%	195,650	91,956	0.3%	12.7%
YUMA-EL CENTRO	47.0%	112,850	53,040	0.2%	12.8%
GREAT FALLS	47.0%	66,190	31,109	0.1%	12.9%
MACON	46.0%	245,910	113,119	0.3%	13.2%
HATTIESBURG-LAUREL	46.0%	111,560	51,318	0.1%	13.4%
BIRMINGHAM	45.0%	738,790	332,456	1.0%	14.3%
TALLAHASSEE-THOMASVILLE	45.0%	272,520	122,634	0.4%	14.7%
BEAUMONT-PORT ARTHUR	45.0%	168,420	75,789	0.2%	14.9%
ALBANY, GA.	45.0%	151,620	68,229	0.2%	15.1%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
CLARKSBURG-WESTON	45.0%	108,980	49,041	0.1%	15.2%
LEXINGTON	44.0%	488,850	215,094	0.6%	15.8%
RENO	44.0%	271,020	119,249	0.3%	16.2%
TRAVERSE CITY-CADILLAC	44.0%	244,050	107,382	0.3%	16.5%
DULUTH-SUPERIOR	44.0%	173,710	76,432	0.2%	16.7%
PHOENIX	43.0%	1,811,330	778,872	2.2%	18.9%
CHARLESTON-HUNTINGTON	43.0%	465,030	199,963	0.6%	19.5%
DES MOINES-AMES	43.0%	431,300	185,459	0.5%	20.0%
HUNTSVILLE-DECATUR, FLORENCE	43.0%	394,010	169,424	0.5%	20.5%
SACRAMENTO-STOCKTON-MODESTO	42.0%	1,388,570	583,199	1.7%	22.2%
SALT LAKE CITY	42.0%	927,540	389,567	1.1%	23.3%
JOHNSTOWN-ALTOONA	42.0%	294,770	123,803	0.4%	23.6%
WAUSAU-RHINELANDER	42.0%	181,280	76,138	0.2%	23.9%
ALEXANDRIA, LA.	42.0%	90,160	37,867	0.1%	24.0%
BUTTE-BOZEMAN	42.0%	66,910	28,102	0.1%	24.0%
OTTUMWA-KIRKSVILLE	42.0%	47,810	20,080	0.1%	24.1%
DENVER	41.0%	1,548,570	634,914	1.8%	25.9%
TUCSON (NOGALES)	41.0%	442,020	181,228	0.5%	26.4%
SAVANNAH	41.0%	335,080	137,383	0.4%	26.8%
BURLINGTON-PLATTSBURGH	41.0%	323,750	132,738	0.4%	27.2%
SOUTH BEND-ELKHART	41.0%	322,090	132,057	0.4%	27.6%
EVANSVILLE	41.0%	287,880	118,031	0.3%	27.9%
LINCOLN & HASTINGS-KEARNEY, PLUS	41.0%	280,310	114,927	0.3%	28.3%
PRESQUE ISLE	41.0%	29,850	12,239	0.0%	28.3%
WACO-TEMPLE-BRYAN	40.0%	353,190	141,276	0.4%	28.7%
SANTA BARBARA-SANTA MARIA-SAN LUIS OBISPO	40.0%	230,830	92,332	0.3%	29.0%
MONTEREY-SALINAS	40.0%	223,620	89,448	0.3%	29.2%
SAN ANGELO	40.0%	55,570	22,228	0.1%	29.3%
SAINT LOUIS	39.0%	1,253,920	489,029	1.4%	30.7%
NASHVILLE	39.0%	1,024,560	399,578	1.1%	31.8%
MEMPHIS	39.0%	669,940	261,277	0.7%	32.6%
TULSA	39.0%	529,100	206,349	0.6%	33.2%
MOBILE-PENSACOLA	39.0%	527,930	205,893	0.6%	33.7%
COLUMBIA, S.C.	39.0%	404,830	157,884	0.5%	34.2%
DAVENPORT-ROCK ISLAND-MOLINE	39.0%	307,050	119,750	0.3%	34.5%
FORT SMITH	39.0%	301,120	117,437	0.3%	34.9%
FORT WAYNE	39.0%	267,710	104,407	0.3%	35.2%
LUBBOCK	39.0%	160,160	62,462	0.2%	35.3%
BILLINGS	39.0%	109,940	42,877	0.1%	35.5%
DOTHAN	39.0%	109,080	42,541	0.1%	35.6%
HARRISONBURG	39.0%	91,620	35,732	0.1%	35.7%
CHAMPAIGN & SPRINGFIELD-DECATUR	38.0%	386,160	146,741	0.4%	36.1%
TRI-CITIES, TENN.-VA.	38.0%	323,640	122,983	0.4%	36.5%
BAKERSFIELD	38.0%	221,920	84,330	0.2%	36.7%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
GREENWOOD-GREENVILLE, MS	38.0%	67,730	25,737	0.1%	36.8%
LOS ANGELES	37.0%	5,569,780	2,060,819	5.9%	42.7%
CHARLOTTE	37.0%	1,140,900	422,133	1.2%	43.9%
NEW ORLEANS	37.0%	643,660	238,154	0.7%	44.6%
GREENVILLE-NEW BERN-WASHINGTON	37.0%	307,610	113,816	0.3%	44.9%
AUGUSTA	37.0%	262,560	97,147	0.3%	45.2%
PEORIA-BLOOMINGTON	37.0%	247,850	91,705	0.3%	45.4%
EUGENE	37.0%	241,270	89,270	0.3%	45.7%
CORPUS CHRISTI	37.0%	203,550	75,314	0.2%	45.9%
BLUEFIELD-BECKLEY-OAK HILL	37.0%	137,380	50,831	0.1%	46.0%
JACKSON, TENN.	37.0%	94,650	35,021	0.1%	46.1%
GREENSBORO-HIGH POINT-WINSTON-SALEM	36.0%	691,200	248,832	0.7%	46.9%
WILKES-BARRE-SCRANTON	36.0%	590,740	212,666	0.6%	47.5%
MADISON	36.0%	378,290	136,184	0.4%	47.8%
LAFAYETTE, LA.	36.0%	229,320	82,555	0.2%	48.1%
SIOUX CITY	36.0%	157,060	56,542	0.2%	48.2%
GAINESVILLE	36.0%	124,730	44,903	0.1%	48.4%
JONESBORO	36.0%	81,300	29,268	0.1%	48.5%
NORTH PLATTE	36.0%	15,180	5,465	0.0%	48.5%
ATLANTA	35.0%	2,292,640	802,424	2.3%	50.8%
JACKSONVILLE	35.0%	669,840	234,444	0.7%	51.4%
CEDAR RAPIDS-WATERLOO & DUBUQUE	35.0%	344,150	120,453	0.3%	51.8%
LANSING	35.0%	252,890	88,512	0.3%	52.0%
CHARLOTTESVILLE	35.0%	74,630	26,121	0.1%	52.1%
CHEYENNE-SCOTTSBLUFF-STERLING	35.0%	56,640	19,824	0.1%	52.2%
ALPENA	35.0%	17,100	5,985	0.0%	52.2%
RALEIGH-DURHAM	34.0%	1,143,420	388,763	1.1%	53.3%
KNOXVILLE	34.0%	527,790	179,449	0.5%	53.8%
CHATTANOOGA	34.0%	366,790	124,709	0.4%	54.2%
EL PASO	34.0%	336,570	114,434	0.3%	54.5%
FARGO-VALLEY CITY	34.0%	246,780	83,905	0.2%	54.7%
LA CROSSE-EAU CLAIRE	34.0%	213,660	72,644	0.2%	54.9%
TOPEKA	34.0%	177,710	60,421	0.2%	55.1%
MARQUETTE	34.0%	85,230	28,978	0.1%	55.2%
PORTLAND, ORE.	33.0%	1,190,010	392,703	1.1%	56.3%
LAS VEGAS	33.0%	737,300	243,309	0.7%	57.0%
RICHMOND-PETERSBURG	33.0%	559,390	184,599	0.5%	57.5%
GREEN BAY-APPLETON	33.0%	445,760	147,101	0.4%	58.0%
MONTGOMERY	33.0%	245,100	80,883	0.2%	58.2%
ROCKFORD	33.0%	184,360	60,839	0.2%	58.4%
ODESSA-MIDLAND	33.0%	146,040	48,193	0.1%	58.5%
ROCHESTER-MASON CITY-AUSTIN	33.0%	145,450	47,999	0.1%	58.6%
DALLAS-FT. WORTH	32.0%	2,571,310	822,819	2.4%	61.0%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
GRAND RAPIDS-KALAMAZOO-BATTLE CREEK	32.0%	722,150	231,088	0.7%	61.7%
FORT MYERS-NAPLES	32.0%	504,240	161,357	0.5%	62.1%
FLINT-SAGINAW-BAY CITY	32.0%	451,880	144,602	0.4%	62.5%
COLUMBUS, GA.	32.0%	215,410	68,931	0.2%	62.7%
ERIE	32.0%	157,730	50,474	0.1%	62.9%
MINOT-BISMARCK-DICKINSON (WILLISTON)	32.0%	145,480	46,554	0.1%	63.0%
RAPID CITY	32.0%	100,120	32,038	0.1%	63.1%
CASPER-RIVERTON	32.0%	56,460	18,067	0.1%	63.1%
SAINT JOSEPH	32.0%	46,690	14,941	0.0%	63.2%
WICHITA1-HUTCHINSON, PLUS	31.0%	454,590	140,923	0.4%	63.6%
HARLINGEN-WESLACO-BROWNSVILLE-MCALLEN	31.0%	361,820	112,164	0.3%	63.9%
CHARLESTON, S.C.	31.0%	311,260	96,491	0.3%	64.2%
PANAMA CITY	31.0%	132,120	40,957	0.1%	64.3%
GRAND JUNCTION-MONTROSE	31.0%	72,970	22,621	0.1%	64.4%
HELENA	31.0%	28,050	8,696	0.0%	64.4%
BUFFALO	30.0%	645,190	193,557	0.6%	64.9%
LAKE CHARLES	30.0%	94,850	28,455	0.1%	65.0%
VICTORIA	30.0%	31,540	9,462	0.0%	65.1%
HOUSTON	29.0%	2,185,260	633,725	1.8%	66.9%
MINNEAPOLIS-ST. PAUL	29.0%	1,721,940	499,363	1.4%	68.3%
CINCINNATI	29.0%	896,090	259,866	0.7%	69.0%
SAN ANTONIO	29.0%	880,690	255,400	0.7%	69.8%
OKLAHOMA CITY	29.0%	712,630	206,663	0.6%	70.4%
FLORENCE-MYRTLE BEACH	29.0%	289,060	83,827	0.2%	70.6%
SIOUX FALLS (MITCHELL)	29.0%	261,530	75,844	0.2%	70.8%
WHEELING-STEUBENVILLE	29.0%	133,120	38,605	0.1%	70.9%
BILOXI-GULFPORT	29.0%	128,150	37,164	0.1%	71.0%
ELMIRA	29.0%	96,600	28,014	0.1%	71.1%
LAREDO	29.0%	72,060	20,897	0.1%	71.2%
LAFAYETTE, IND.	29.0%	67,260	19,505	0.1%	71.2%
ZANESVILLE	29.0%	33,140	9,611	0.0%	71.3%
CHICAGO	28.0%	3,493,480	978,174	2.8%	74.1%
SAN FRANCISCO-OAKLAND-SAN JOSE	28.0%	2,506,510	701,823	2.0%	76.1%
INDIANAPOLIS	28.0%	1,109,970	310,792	0.9%	76.9%
YOUNGSTOWN	28.0%	263,850	73,878	0.2%	77.2%
WILMINGTON	28.0%	190,730	53,404	0.2%	77.3%
KANSAS CITY	27.0%	939,740	253,730	0.7%	78.0%
HARRISBURG-LANCASTER-LEBANON-YORK	27.0%	729,440	196,949	0.6%	78.6%
LOUISVILLE	27.0%	674,050	181,994	0.5%	79.1%
TOLEDO	27.0%	426,280	115,096	0.3%	79.4%
MANKATO	27.0%	53,720	14,504	0.0%	79.5%
ORLANDO-DAYTONA BEACH-MELBOURNE	26.0%	1,465,460	381,020	1.1%	80.6%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
AUSTIN, TEX.	26.0%	686,830	178,576	0.5%	81.1%
DAYTON	26.0%	493,600	128,336	0.4%	81.5%
PORTLAND-AUBURN	26.0%	401,370	104,356	0.3%	81.8%
WATERTOWN	26.0%	93,090	24,203	0.1%	81.8%
BEND	26.0%	62,620	16,281	0.0%	81.9%
GLENDIVE	26.0%	4,180	1,087	0.0%	81.9%
MIAMI-FT. LAUDERDALE	25.0%	1,583,800	395,950	1.1%	83.0%
CLEVELAND	25.0%	1,514,170	378,543	1.1%	84.1%
OMAHA	25.0%	415,510	103,878	0.3%	84.4%
BATON ROUGE	25.0%	333,010	83,253	0.2%	84.6%
PALM SPRINGS	25.0%	158,440	39,610	0.1%	84.7%
BINGHAMTON	25.0%	136,730	34,183	0.1%	84.8%
PARKERSBURG	25.0%	63,120	15,780	0.0%	84.9%
EUREKA	25.0%	61,180	15,295	0.0%	84.9%
PITTSBURGH	24.0%	1,171,490	281,158	0.8%	85.7%
WEST PALM BEACH-FT. PIERCE	24.0%	788,020	189,125	0.5%	86.3%
NORFOLK-PORTSMOUTH-NEWPORT NEWS	24.0%	718,750	172,500	0.5%	86.8%
COLUMBUS, OHIO	23.0%	932,680	214,516	0.6%	87.4%
BOWLING GREEN	23.0%	79,990	18,398	0.1%	87.4%
WASHINGTON, D.C.	22.0%	2,360,180	519,240	1.5%	88.9%
DETROIT	22.0%	1,842,650	405,383	1.2%	90.1%
UTICA	22.0%	104,750	23,045	0.1%	90.1%
LIMA	22.0%	39,350	8,657	0.0%	90.2%
BALTIMORE	21.0%	1,097,310	230,435	0.7%	90.8%
ANCHORAGE	21.0%	155,600	32,676	0.1%	90.9%
SEATTLE-TACOMA	20.0%	1,811,420	362,284	1.0%	91.9%
MILWAUKEE	20.0%	907,660	181,532	0.5%	92.5%
ROCHESTER, N.Y.	20.0%	396,790	79,358	0.2%	92.7%
SALISBURY	20.0%	159,640	31,928	0.1%	92.8%
ALBANY-SCHENECTADY-TROY	19.0%	551,120	104,713	0.3%	93.1%
SYRACUSE	18.0%	386,090	69,496	0.2%	93.3%
SAN DIEGO	16.0%	1,077,600	172,416	0.5%	93.8%
SPRINGFIELD-HOLYOKE	16.0%	257,080	41,133	0.1%	93.9%
PHILADELPHIA	15.0%	2,993,370	449,006	1.3%	95.2%
TAMPA-ST. PETERSBURG, SARASOTA	15.0%	1,788,240	268,236	0.8%	95.9%
HARTFORD & NEW HAVEN	15.0%	1,006,280	150,942	0.4%	96.4%
BOSTON	14.0%	2,379,690	333,157	1.0%	97.3%
NEW YORK	12.0%	7,387,810	886,537	2.5%	99.9%
PROVIDENCE-NEW BEDFORD	8.0%	620,010	49,601	0.1%	100.0%

Figure 44: Comparison of DMA ranking by satellite penetration rate and number of satellite subscribers – 2013

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
COLUMBUS-TUPELO-WEST POINT	62.0%	184,990	114,694	0.3%	0.3%
SHREVEPORT-TEXARKANA	61.0%	384,410	234,490	0.7%	1.0%
MERIDIAN	60.0%	68,860	41,316	0.1%	1.1%
PADUCAH-CAPE GIRARDEAU-HARRISBG-MT VERNON	59.0%	388,340	229,121	0.6%	1.7%
SHERMAN-ADA	58.0%	126,930	73,619	0.2%	2.0%
SPRINGFIELD, MO.	56.0%	414,570	232,159	0.7%	2.6%
CHICO-REDDING	56.0%	191,500	107,240	0.3%	2.9%
ABILENE-SWEETWATER	56.0%	114,080	63,885	0.2%	3.1%
COLUMBIA - JEFFERSON CITY	55.0%	173,640	95,502	0.3%	3.4%
TYLER-LONGVIEW (LUFKIN & NACOGDOCHES)	54.0%	268,150	144,801	0.4%	3.8%
ROANOKE-LYNCHBURG	53.0%	445,470	236,099	0.7%	4.4%
WICHITA FALLS & LAWTON	53.0%	158,500	84,005	0.2%	4.7%
LITTLE ROCK-PINE BLUFF	52.0%	561,760	292,115	0.8%	5.5%
JACKSON, MISS.	52.0%	331,500	172,380	0.5%	6.0%
BOISE	52.0%	259,090	134,727	0.4%	6.4%
TERRE HAUTE	52.0%	139,600	72,592	0.2%	6.6%
MACON	51.0%	241,170	122,997	0.3%	6.9%
MONROE-EL DORADO	51.0%	175,960	89,740	0.3%	7.2%
ALBANY, GA.	51.0%	150,110	76,556	0.2%	7.4%
QUINCY-HANNIBAL-KEOKUK	51.0%	103,520	52,795	0.1%	7.5%
FRESNO-VISALIA	50.0%	576,820	288,410	0.8%	8.4%
SPOKANE	50.0%	420,640	210,320	0.6%	8.9%
YAKIMA-PASCO-RICHLAND-KENNEWICK	50.0%	231,950	115,975	0.3%	9.3%
MEDFORD-KLAMATH FALLS	50.0%	167,820	83,910	0.2%	9.5%
AMARILLO	49.0%	197,110	96,584	0.3%	9.8%
JOPLIN-PITTSBURG	49.0%	151,200	74,088	0.2%	10.0%
YUMA-EL CENTRO	49.0%	113,230	55,483	0.2%	10.1%
HATTIESBURG-LAUREL	49.0%	109,950	53,876	0.2%	10.3%
GREAT FALLS	49.0%	65,930	32,306	0.1%	10.4%
TWIN FALLS	49.0%	64,100	31,409	0.1%	10.5%
ALBUQUERQUE-SANTA FE	48.0%	691,450	331,896	0.9%	11.4%
IDAHO FALLS-POCATELLO	48.0%	125,710	60,341	0.2%	11.6%
MISSOULA	48.0%	113,010	54,245	0.2%	11.7%
CLARKSBURG-WESTON	48.0%	106,480	51,110	0.1%	11.9%
GREENVILLE-SPARTANBURG-ASHEVILLE-ANDRSN	47.0%	846,030	397,634	1.1%	13.0%
LEXINGTON	47.0%	485,630	228,246	0.6%	13.6%
BEAUMONT-PORT ARTHUR	47.0%	167,110	78,542	0.2%	13.9%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
BANGOR	47.0%	138,040	64,879	0.2%	14.1%
BIRMINGHAM	46.0%	717,530	330,064	0.9%	15.0%
DES MOINES-AMES	46.0%	427,860	196,816	0.6%	15.5%
COLORADO SPRINGS-PUEBLO	46.0%	343,990	158,235	0.4%	16.0%
PHOENIX	45.0%	1,812,040	815,418	2.3%	18.3%
SOUTH BEND-ELKHART	45.0%	319,860	143,937	0.4%	18.7%
LINCOLN & HASTINGS-KEARNEY, PLUS	45.0%	276,790	124,556	0.4%	19.0%
HUNTSVILLE-DECATUR, FLORENCE	44.0%	390,590	171,860	0.5%	19.5%
EVANSVILLE	44.0%	284,040	124,978	0.4%	19.9%
TALLAHASSEE-THOMASVILLE	44.0%	273,120	120,173	0.3%	20.2%
DULUTH-SUPERIOR	44.0%	169,610	74,628	0.2%	20.4%
ALEXANDRIA, LA.	44.0%	89,280	39,283	0.1%	20.5%
SACRAMENTO-STOCKTON-MODESTO	43.0%	1,387,710	596,715	1.7%	22.2%
SALT LAKE CITY	43.0%	917,370	394,469	1.1%	23.3%
CHARLESTON-HUNTINGTON	43.0%	455,490	195,861	0.6%	23.9%
TUCSON (NOGALES)	43.0%	438,440	188,529	0.5%	24.4%
SAVANNAH	43.0%	334,750	143,943	0.4%	24.8%
DAVENPORT-ROCK ISLAND-MOLINE	43.0%	303,800	130,634	0.4%	25.2%
RENO	43.0%	265,600	114,208	0.3%	25.5%
TRAVERSE CITY-CADILLAC	43.0%	241,800	103,974	0.3%	25.8%
BUTTE-BOZEMAN	43.0%	67,180	28,887	0.1%	25.9%
OTTUMWA-KIRKSVILLE	43.0%	46,730	20,094	0.1%	26.0%
PRESQUE ISLE	43.0%	29,250	12,578	0.0%	26.0%
MOBILE-PENSACOLA	42.0%	525,990	220,916	0.6%	26.6%
WACO-TEMPLE-BRYAN	42.0%	349,540	146,807	0.4%	27.0%
TRI-CITIES, TENN.-VA.	42.0%	319,060	134,005	0.4%	27.4%
JOHNSTOWN-ALTOONA	42.0%	288,100	121,002	0.3%	27.7%
FORT WAYNE	42.0%	265,390	111,464	0.3%	28.1%
SANTA BARBARA-SANTA MARIA-SAN LUIS OBISPO	42.0%	231,950	97,419	0.3%	28.3%
WAUSAU-RHINELANDER	42.0%	179,450	75,369	0.2%	28.5%
DENVER	41.0%	1,566,460	642,249	1.8%	30.4%
NASHVILLE	41.0%	1,014,910	416,113	1.2%	31.5%
BURLINGTON-PLATTSBURGH	41.0%	316,910	129,933	0.4%	31.9%
FORT SMITH	41.0%	297,590	122,012	0.3%	32.2%
MONTEREY-SALINAS	41.0%	224,240	91,938	0.3%	32.5%
CORPUS CHRISTI	41.0%	203,730	83,529	0.2%	32.7%
DOTHAN	41.0%	107,110	43,915	0.1%	32.9%
HARRISONBURG	41.0%	90,260	37,007	0.1%	33.0%
SAN ANGELO	41.0%	55,820	22,886	0.1%	33.0%
MEMPHIS	40.0%	662,830	265,132	0.7%	33.8%
CHAMPAIGN & SPRINGFIELD-DECATUR	40.0%	378,720	151,488	0.4%	34.2%
GREENVILLE-NEW BERN-WASHINGTON	40.0%	303,280	121,312	0.3%	34.6%
BAKERSFIELD	40.0%	221,740	88,696	0.3%	34.8%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
LUBBOCK	40.0%	159,840	63,936	0.2%	35.0%
BLUEFIELD-BECKLEY-OAK HILL	40.0%	134,410	53,764	0.2%	35.1%
SAINT JOSEPH	40.0%	46,180	18,472	0.1%	35.2%
AUGUSTA	39.0%	257,730	100,515	0.3%	35.5%
GAINESVILLE	39.0%	123,430	48,138	0.1%	35.6%
GREENWOOD-GREENVILLE, MS	39.0%	66,410	25,900	0.1%	35.7%
SAINT LOUIS	38.0%	1,243,490	472,526	1.3%	37.0%
TULSA	38.0%	526,960	200,245	0.6%	37.6%
EL PASO	38.0%	339,130	128,869	0.4%	37.9%
EUGENE	38.0%	235,570	89,517	0.3%	38.2%
LA CROSSE-EAU CLAIRE	38.0%	211,670	80,435	0.2%	38.4%
BILLINGS	38.0%	109,730	41,697	0.1%	38.5%
JACKSON, TENN.	38.0%	93,090	35,374	0.1%	38.6%
JONESBORO	38.0%	80,740	30,681	0.1%	38.7%
ALPENA	38.0%	16,910	6,426	0.0%	38.7%
CHARLOTTE	37.0%	1,136,420	420,475	1.2%	39.9%
KNOXVILLE	37.0%	520,890	192,729	0.5%	40.5%
COLUMBIA, S.C.	37.0%	398,510	147,449	0.4%	40.9%
MADISON	37.0%	376,670	139,368	0.4%	41.3%
HARLINGEN-WESLACO-BROWNSVILLE-MCALLEN	37.0%	364,160	134,739	0.4%	41.7%
CEDAR RAPIDS-WATERLOO & DUBUQUE	37.0%	342,610	126,766	0.4%	42.0%
PEORIA-BLOOMINGTON	37.0%	244,050	90,299	0.3%	42.3%
LAFAYETTE, LA.	37.0%	229,320	84,848	0.2%	42.5%
SIOUX CITY	37.0%	154,830	57,287	0.2%	42.7%
ODESSA-MIDLAND	37.0%	147,730	54,660	0.2%	42.8%
NORTH PLATTE	37.0%	14,720	5,446	0.0%	42.8%
LOS ANGELES	36.0%	5,613,460	2,020,846	5.7%	48.6%
NEW ORLEANS	36.0%	641,550	230,958	0.7%	49.2%
WILKES-BARRE-SCRANTON	36.0%	581,020	209,167	0.6%	49.8%
LANSING	36.0%	251,140	90,410	0.3%	50.0%
COLUMBUS, GA.	36.0%	216,920	78,091	0.2%	50.3%
ROCKFORD	36.0%	179,240	64,526	0.2%	50.5%
ERIE	36.0%	155,190	55,868	0.2%	50.6%
CHARLOTTESVILLE	36.0%	74,340	26,762	0.1%	50.7%
CHEYENNE-SCOTTSBLUFF-STERLING	36.0%	56,350	20,286	0.1%	50.7%
LAS VEGAS	35.0%	718,990	251,647	0.7%	51.5%
GREENSBORO-HIGH POINT-WINSTON-SALEM	35.0%	695,100	243,285	0.7%	52.1%
FARGO-VALLEY CITY	35.0%	243,890	85,362	0.2%	52.4%
TOPEKA	35.0%	176,160	61,656	0.2%	52.6%
MARQUETTE	35.0%	84,640	29,624	0.1%	52.6%
RICHMOND-PETERSBURG	34.0%	553,390	188,153	0.5%	53.2%
MONTGOMERY	34.0%	241,930	82,256	0.2%	53.4%
PANAMA CITY	34.0%	129,390	43,993	0.1%	53.5%
HELENA	34.0%	28,260	9,608	0.0%	53.6%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
DALLAS-FT. WORTH	33.0%	2,588,020	854,047	2.4%	56.0%
RALEIGH-DURHAM	33.0%	1,150,350	379,616	1.1%	57.0%
CHATTANOOGA	33.0%	353,710	116,724	0.3%	57.4%
ROCHESTER-MASON CITY-AUSTIN	33.0%	143,330	47,299	0.1%	57.5%
ELMIRA	33.0%	95,530	31,525	0.1%	57.6%
CASPER-RIVERTON	33.0%	55,270	18,239	0.1%	57.6%
VICTORIA	33.0%	31,560	10,415	0.0%	57.7%
ATLANTA	32.0%	2,326,840	744,589	2.1%	59.8%
PORTLAND, ORE.	32.0%	1,182,180	378,298	1.1%	60.8%
GRAND RAPIDS-KALAMAZOO-BATTLE CREEK	32.0%	720,150	230,448	0.7%	61.5%
JACKSONVILLE	32.0%	659,170	210,934	0.6%	62.1%
FORT MYERS-NAPLES	32.0%	502,050	160,656	0.5%	62.5%
WICHITA1-HUTCHINSON, PLUS	32.0%	450,300	144,096	0.4%	62.9%
FLINT-SAGINAW-BAY CITY	32.0%	446,010	142,723	0.4%	63.3%
GREEN BAY-APPLETON	32.0%	441,800	141,376	0.4%	63.7%
WHEELING-STEUBENVILLE	32.0%	130,110	41,635	0.1%	63.9%
RAPID CITY	32.0%	98,020	31,366	0.1%	63.9%
GRAND JUNCTION-MONTROSE	32.0%	70,580	22,586	0.1%	64.0%
LAFAYETTE, IND.	32.0%	66,240	21,197	0.1%	64.1%
OKLAHOMA CITY	31.0%	718,770	222,819	0.6%	64.7%
SIOUX FALLS (MITCHELL)	31.0%	258,460	80,123	0.2%	64.9%
WILMINGTON	31.0%	188,420	58,410	0.2%	65.1%
MINOT-BISMARCK-DICKINSON (WILLISTON)	31.0%	150,000	46,500	0.1%	65.2%
LAKE CHARLES	31.0%	94,610	29,329	0.1%	65.3%
EUREKA	31.0%	59,610	18,479	0.1%	65.4%
SAN FRANCISCO-OAKLAND-SAN JOSE	30.0%	2,502,030	750,609	2.1%	67.5%
HOUSTON	30.0%	2,215,650	664,695	1.9%	69.3%
MINNEAPOLIS-ST. PAUL	30.0%	1,728,050	518,415	1.5%	70.8%
INDIANAPOLIS	30.0%	1,089,700	326,910	0.9%	71.7%
CINCINNATI	30.0%	897,890	269,367	0.8%	72.5%
PORTLAND-AUBURN	30.0%	389,530	116,859	0.3%	72.8%
CHARLESTON, S.C.	30.0%	316,080	94,824	0.3%	73.1%
FLORENCE-MYRTLE BEACH	30.0%	285,550	85,665	0.2%	73.3%
SAN ANTONIO	29.0%	881,050	255,505	0.7%	74.1%
BUFFALO	29.0%	632,150	183,324	0.5%	74.6%
YOUNGSTOWN	29.0%	260,000	75,400	0.2%	74.8%
PALM SPRINGS	29.0%	154,560	44,822	0.1%	74.9%
BILOXI-GULFPORT	29.0%	128,300	37,207	0.1%	75.0%
WATERTOWN	29.0%	92,590	26,851	0.1%	75.1%
LAREDO	29.0%	72,590	21,051	0.1%	75.2%
PARKERSBURG	29.0%	62,620	18,160	0.1%	75.2%
GLENDIVE	29.0%	4,050	1,175	0.0%	75.2%
CHICAGO	28.0%	3,484,800	975,744	2.8%	78.0%
KANSAS CITY	28.0%	931,320	260,770	0.7%	78.7%

DMA	Penetration rate	Households	Satellite subscribers		
			Total	Percentage	Cumulative
HARRISBURG-LANCASTER-LEBANON-YORK	28.0%	716,990	200,757	0.6%	79.3%
ZANESVILLE	28.0%	32,940	9,223	0.0%	79.3%
ORLANDO-DAYTONA BEACH-MELBOURNE	27.0%	1,453,170	392,356	1.1%	80.4%
LOUISVILLE	27.0%	670,880	181,138	0.5%	80.9%
DAYTON	27.0%	498,270	134,533	0.4%	81.3%
OMAHA	27.0%	414,060	111,796	0.3%	81.6%
TOLEDO	27.0%	409,550	110,579	0.3%	81.9%
BATON ROUGE	27.0%	329,620	88,997	0.3%	82.2%
BEND	27.0%	62,950	16,997	0.0%	82.2%
MANKATO	27.0%	52,530	14,183	0.0%	82.3%
CLEVELAND	26.0%	1,485,140	386,136	1.1%	83.3%
AUSTIN, TEX.	26.0%	705,280	183,373	0.5%	83.9%
SALISBURY	26.0%	157,830	41,036	0.1%	84.0%
LIMA	26.0%	51,240	13,322	0.0%	84.0%
COLUMBUS, OHIO	25.0%	930,460	232,615	0.7%	84.7%
NORFOLK-PORTSMOUTH-NEWPORT NEWS	25.0%	709,730	177,433	0.5%	85.2%
ANCHORAGE	25.0%	156,280	39,070	0.1%	85.3%
BINGHAMTON	25.0%	133,420	33,355	0.1%	85.4%
BOWLING GREEN	24.0%	78,780	18,907	0.1%	85.4%
SEATTLE-TACOMA	23.0%	1,818,900	418,347	1.2%	86.6%
MIAMI-FT. LAUDERDALE	23.0%	1,621,130	372,860	1.1%	87.7%
PITTSBURGH	23.0%	1,165,740	268,120	0.8%	88.4%
WEST PALM BEACH-FT. PIERCE	23.0%	794,310	182,691	0.5%	88.9%
WASHINGTON, D.C.	22.0%	2,359,160	519,015	1.5%	90.4%
ROCHESTER, N.Y.	22.0%	395,680	87,050	0.2%	90.6%
UTICA	22.0%	102,890	22,636	0.1%	90.7%
DETROIT	21.0%	1,845,920	387,643	1.1%	91.8%
BALTIMORE	21.0%	1,085,070	227,865	0.6%	92.4%
MILWAUKEE	21.0%	902,190	189,460	0.5%	93.0%
ALBANY-SCHENECTADY-TROY	19.0%	540,050	102,610	0.3%	93.3%
SAN DIEGO	18.0%	1,075,120	193,522	0.5%	93.8%
SYRACUSE	18.0%	377,550	67,959	0.2%	94.0%
HARTFORD & NEW HAVEN	16.0%	996,550	159,448	0.4%	94.5%
SPRINGFIELD-HOLYOKE	16.0%	252,950	40,472	0.1%	94.6%
PHILADELPHIA	15.0%	2,949,310	442,397	1.2%	95.8%
TAMPA-ST. PETERSBURG, SARASOTA	15.0%	1,806,560	270,984	0.8%	96.6%
BOSTON	14.0%	2,366,690	331,337	0.9%	97.5%
NEW YORK	11.0%	7,384,340	812,277	2.3%	99.8%
PROVIDENCE-NEW BEDFORD	11.0%	606,400	66,704	0.2%	100.0%

Appendix H. Relationship between Gracenote's program type and Dr. Gray's categorization

Figure 45: Relationship between Gracenote's program type and Dr. Gray's categorization (2011 broadcasts)

Program type	Gray categorization				
	Commercial	Devotional	Program supplier	JSC	Total
CARTOON	0	0	15,643	0	15,643
CHILDREN'S SHOW	0	0	10,874	0	10,874
CHILDREN'S SPECIAL	0	0	689	0	689
DAYTIME SOAP	0	0	27,086	0	27,086
FINANCE	390	0	2,913	0	3,303
FIRST-RUN SYNDICATION	0	0	603	0	603
GAME SHOW	0	0	38,177	0	38,177
HEALTH	119	0	1,176	0	1,295
HOBBIES & CRAFTS	4	0	18	0	22
INSTRUCTIONAL	2	0	3,883	0	3,885
MINI-SERIES	0	0	4	0	4
MOVIE	0	1	6,814	0	6,815
MUSIC	70	1	3,358	0	3,429
MUSIC SPECIAL	17	4	591	0	612
NETWORK SERIES	0	0	53,229	0	53,229
NEWS	154,271	0	44,044	0	198,315
OTHER	11,211	52	108,162	0	119,425
PLAYOFF SPORTS	11	0	93	1,650	1,754
PSEUDO-SPORTS	20	0	87	0	107
PUBLIC AFFAIRS	2,621	1	2,552	0	5,174
RELIGIOUS	0	11,166	0	0	11,166
SPECIAL	1,190	244	2,742	0	4,176
SPORTING EVENT	13	0	9,578	25	9,616
SPORTS ANTHOLOGY	0	0	2,067	0	2,067
SPORTS-RELATED	3,123	0	10,101	21	13,245
SYNDICATED	0	0	292,602	0	292,602
TALK SHOW	0	1,529	157,337	0	158,866
TEAM VS. TEAM	5	0	240	4,853	5,098
TV MOVIE	0	0	291	0	291
TOTAL	**173,067**	**12,998**	**794,954**	**6,549**	**987,568**

Figure 46: Relationship between Gracenote's program type and Dr. Gray's categorization (2012 broadcasts)

Program type	Gray categorization				
	Commercial	Devotional	Program supplier	JSC	Total
CARTOON	0	0	11,832	0	11,832
CHILDREN'S SHOW	0	0	11,895	0	11,895
CHILDREN'S SPECIAL	0	0	681	0	681
DAYTIME SOAP	0	0	18,838	0	18,838
FINANCE	376	0	5,667	0	6,043
GAME SHOW	0	0	39,587	0	39,587
HEALTH	73	0	993	0	1,066
INSTRUCTIONAL	28	0	3,529	0	3,557
MINI-SERIES	0	0	52	0	52
MOVIE	0	0	7,462	0	7,462
MUSIC	128	9	3,762	0	3,899
MUSIC SPECIAL	26	7	657	0	690
NETWORK SERIES	0	0	58,269	0	58,269
NEWS	147,506	0	44,922	0	192,428
OTHER	12,455	18	107,018	0	119,491
PLAYOFF SPORTS	24	0	0	1,770	1,794
PSEUDO-SPORTS	21	0	256	0	277
PUBLIC AFFAIRS	2,744	0	226	0	2,970
RELIGIOUS	0	13,027	6	0	13,033
SPECIAL	893	268	2,799	0	3,960
SPORTING EVENT	1	0	6,644	63	6,708
SPORTS ANTHOLOGY	0	0	1,823	0	1,823
SPORTS-RELATED	3,103	0	12,413	0	15,516
SYNDICATED	0	0	289,112	0	289,112
TALK SHOW	0	1,231	169,574	0	170,805
TEAM VS. TEAM	11	0	190	4,956	5,157
TV MOVIE	0	0	200	0	200
TOTAL	**167,389**	**14,560**	**798,407**	**6,789**	**987,145**

Figure 47: Relationship between Gracenote's program type and Dr. Gray's categorization (2013 broadcasts)

Program type	Gray categorization				
	Commercial	Devotional	Program supplier	JSC	Total
CARTOON	0	0	10,842	0	10,842
CHILDREN'S SHOW	0	0	7,926	0	7,926
CHILDREN'S SPECIAL	0	0	507	0	507
DAYTIME SOAP	0	0	16,631	0	16,631
FINANCE	680	0	4,781	0	5,461
GAME SHOW	0	0	35,474	0	35,474
HEALTH	41	0	1,392	0	1,433
INSTRUCTIONAL	0	0	3,126	0	3,126
MOVIE	0	0	5,944	0	5,944
MUSIC	110	10	3,045	0	3,165
MUSIC SPECIAL	25	0	763	0	788
NETWORK SERIES	0	0	54,389	0	54,389
NEWS	131,685	0	41,694	0	173,379
OTHER	9,792	2	100,284	0	110,078
PLAYOFF SPORTS	8	0	42	1,521	1,571
PSEUDO-SPORTS	0	0	299	0	299
PUBLIC AFFAIRS	1,954	0	610	0	2,564
RELIGIOUS	0	10,371	321	0	10,692
SPECIAL	910	310	2,909	0	4,129
SPORTING EVENT	0	0	4,922	17	4,939
SPORTS ANTHOLOGY	0	0	1,666	0	1,666
SPORTS-RELATED	3,046	0	10,255	0	13,301
SYNDICATED	0	92	247,728	0	247,820
TALK SHOW	0	969	154,849	0	155,818
TEAM VS. TEAM	0	0	263	4,420	4,683
TV MOVIE	0	0	131	0	131
TOTAL	**148,251**	**11,754**	**710,793**	**5,958**	**876,756**

DECLARATION OF CHRISTOPHER J. BENNETT

I declare under penalty of perjury that the foregoing is true and correct.

Executed on: August 26, 2019

Christopher J. Bennett

Before the
COPYRIGHT ROYALTY JUDGES
WASHINGTON, DC

	)	
In re	)	
	)	**CONSOLIDATED DOCKET NO.**
Distribution of Satellite Royalty Funds	)	**No. 14-CRB-0011-SD (2010-13)**
	)	

REBUTTAL TESTIMONY OF RANDAL D. HEEB, PhD

August 26, 2019

Table of contents

I. Introduction

I.A. Summary of qualifications and experience

(1) I am a Partner in the economic consulting firm of Bates White, LLC, where I am the leader of the firm's Intellectual Property Practice and co-leader in the firm's Antitrust and Competition Practice. My educational background, experience, and credentials have been presented as part of my Written Direct Testimony submitted in this proceeding on March 22, 2019. Updated information about my previous testifying experience and my professional experience as an economist, including publications and affiliations, is included in my updated curriculum vitae, attached as Appendix A.

I.B. Executive Summary

I.B.1. Scope of charge

(2) I have been asked by counsel for the Commercial Television (CTV) Claimants to evaluate the arguments of Dr. Erkan Erdem and Dr. Daniel Rubinfeld, witnesses presented on behalf of the Devotional Claimants.

I.B.2. Summary of opinions

(3) I base my opinions in this matter on my experience and expertise and on my review and analysis of the written testimony of Dr. Erdem and Dr. Rubinfeld, including supporting materials submitted with that testimony, as well as the written and oral testimony of Dr. Gregory Crawford and Dr. Erdem in the cable proceeding.[1] I also reviewed the written testimony of Dr. Christopher J. Bennett in the cable proceeding, and his testimony and backup materials in this proceeding.

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[1] *See* Written Direct Testimony of Erkan Erdem, Ph.D. In re Distribution of Satellite Royalty Funds, No. 14-CRB-0011-SD (2010-13) (filed March 22, 2019, amended June 7, 2019) (hereinafter "Erdem Amended Satellite WDT"); Written Direct Testimony of Daniel L. Rubinfeld, In re Distribution of Satellite Royalty Funds, No. 14-CRB-0011-SD (2010-13) (filed March 22, 2019, amended June 7, 2019) (hereinafter "Rubinfeld Amended WDT"); Testimony of Gregory Crawford, Ph.D. In re Distribution of Cable Royalty Funds, No. 14-CRB-0010-CD (2010-13) (filed December 22, 2016, corrected April 11, 2017) (hereinafter "Crawford Corrected Cable Testimony"); Testimony of Erkan Erdem, Ph.D. In re Distribution of the 2010-2013 Cable Royalty Funds, No. 14-CRB-0010-CD (2010-13) (filed March 9, 2017) (hereinafter "Erdem Cable Testimony"); Corrected Testimony of Christopher J. Bennett, Ph.D. In re Distribution of Cable Royalty Funds, No. 14-CRB-0010-CD (2010-13) (filed December 22, 2016, corrected April 11, 2017) (hereinafter "Bennett CWDT"); Testimony of Christopher J. Bennett, Ph.D. In re Distribution of Satellite Royalty Funds, No. 14-CRB-0011-SD (2010-13) (filed March 22, 2019).

(4) After reviewing Dr. Erdem and Dr. Rubinfeld's amended direct testimony, including those portions responding to my written direct testimony, it remains my opinion that it is infeasible to directly apply Dr. Crawford's regression methodology to obtain satellite specific regression coefficients directly from the satellite data. This is because the key characteristic of the cable data exploited by Dr. Crawford's methodology in the cable context is the existence of distant signal royalties and programming data at the subscriber group level. The structure of the satellite royalty data do not allow the implementation of the Crawford methodology.

(5) Dr. Erdem and I agree that satellite data are inadequate to reliably estimate satellite-specific claimant minute regression coefficients using the Crawford methodology. I reached that conclusion by examination of the Crawford regression methodology as described in the record of the cable proceeding, and by examining the structure of the data available in the cable proceeding. Dr. Erdem reaches the same conclusion, and goes further to demonstrate by example the futility of attempting the cable regression using satellite data.

(6) It also remains my opinion that the coefficients on claimant group minutes obtained from the cable regression and reported by Dr. Crawford in his testimony in that proceeding reliably reflect relative values of claimant group minutes in the cable context. Because the true relative valuations in both contexts reflect satellite and cable system operators' common objectives of cost-effectively offering valuable programming content to their current and potential subscribers, the true relative marginal valuations of claimant group minutes are likely very similar in the two contexts. On this point, Dr. Erdem and I agree.

(7) Because the relative values of satellite claimant minutes are likely very similar to the relative values for cable minutes, it is my opinion that the cable coefficients are appropriate to use for allocation purposes for satellite distant signals as well, using satellite-specific compensable minutes data along with cable-derived estimates of claimant group coefficients.

(8) Dr. Erdem criticized Dr. Crawford's regression in the cable proceeding, and renews the same and similar objections to that methodology this satellite proceeding. In his amended testimony, he criticizes the satellite royalty allocation methodology that I advocated in my direct testimony in this matter, arguing that the claimant coefficients that were deemed by the Judges to be reasonable and reliable for allocation purposes in the cable proceeding were and are, on the contrary, unreliable. Therefore, he argues, I should have not have used those cable coefficients in the satellite allocation. I strongly disagree.

(9) Dr. Erdem offered a variety of perturbations of the Crawford cable regressions (using cable data), attempting to prove or illustrate his claims regarding the reliability of the cable regressions. I have examined all of Dr. Erdem's models and tests. All of those experiments are poorly constructed and improperly interpreted. With only one exception, Dr. Erdem's modeling experiments shed no

additional light on the reliability or robustness of Dr. Crawford's regression methodology, which appears to have been thoroughly examined in the cable proceeding. The only exception is Dr. Erdem's test of an alternative standard error clustering assumption, which when properly interpreted, confirms that Dr. Crawford's cable regressions and conclusions are robust to an alternative clustering assumption advocated by Dr. Erdem. I discuss Dr. Erdem's modeling experiments at length in the testimony below.

(10) I agree with the most important insight that derives from Dr. Erdem's attempt to construct a reliable regression using the satellite data—namely that it is infeasible to implement Dr. Crawford's cable regression methodology using satellite data. However, Dr. Erdem and Dr. Rubinfeld repeatedly attempt to argue by analogy that the inadequacy of the satellite data and resulting infeasibility of estimating the Crawford regressions in the satellite context somehow imply by analogy that the cable regression is unreliable. In my opinion, no insights about the reliability of the cable regression or the cable regression coefficients can be derived from Dr. Erdem's failed attempt to implement a satellite regression.

(11) Dr. Rubinfeld argues that Dr. Crawford's cable regression methodology (and Waldfogel-type regressions as presented in previous proceedings generally) fail to meet his methodological expectations, particularly those related to "hedonic regressions." A principal argument that he makes is that the absence of price variation and the fact that prices are set by regulation render the Crawford model "unworkable." I strongly disagree. Empirical economists use similar techniques as those employed by Dr. Crawford's methodology in a wide variety of settings precisely to obtain insights about the relative value of alternative choices in situations in which market determined prices are unavailable. I provide a variety of examples of such economic research published in the profession's best academic journals.

(12) In my opinion, the Crawford methodology is well-founded and appropriately implements the economic intuition explained in the Judges' cable decision adopting that methodology. In my opinion, that methodology recovers a reliable measure of the relative value of claimant minutes.

(13) In my opinion, Dr. Rubinfeld's desire to explore the deep theoretical foundations of the correlations measured by Dr. Crawford's methodology, like some of his other specific criticisms and suggestions, illustrates the adage that the best may be the enemy of the good. While I laud Dr. Rubinfeld's instinct to suggest improvements to any methodology he examines, in my opinion the practical utility and reliability of the Crawford regression methodology in its current form strongly recommend my use of the resulting cable regression coefficients, in conjunction with the satellite compensable minutes data, to determine reasonable and reliable satellite royalty allocation shares.

(14) Further elaboration of these opinions, as well as my remaining opinions in this matter, are discussed throughout this testimony.

II. Rebuttal to Dr. Erdem

II.A. Points of agreement with Dr. Erdem

(15) Dr. Erdem and I agree that the relative valuations of claimant group minutes in the cable and satellite context are likely to be very similar.[2] However, Dr. Erdem goes further to argue that Dr. Crawford's regression specification was invalid or inappropriate in the cable context and that therefore the measures of relative value obtained by regression analysis in the cable context should not be used to inform the allocation of royalty shares in the satellite context.[3] On this latter point, I disagree.

(16) The regression specifications that Dr. Erdem implements using satellite data are inappropriate for use in this or any other context and yield results that are uninformative as to the allocation of satellite distant signal royalties.[4] On this point Dr. Erdem and I agree. Indeed, Dr. Erdem's results illustrate the more general observation that I made in my written testimony, that "[i]n the satellite context, data limitations prevent a direct application of Dr. Crawford's methodology. Obtaining satellite specific regression coefficients on minutes directly from satellite data is infeasible […]."[5]

(17) The reason that Dr. Crawford's econometric estimation approach cannot be re-implemented directly using satellite data is that this strategy in the cable context relies on variation in the distant signal carriage choices made by system operators across subscriber groups, within systems and accounting periods, and variation in the resulting royalties that they paid.[6] There is no such variation available in the satellite context, because there are no comparable groupings of subscribers, and there is no information about which distant signals are available to which subscribers within a satellite system.[7]

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2 Erdem Amended Satellite WDT, ¶ 34. ("[I] conclude that the decision-making process to determine relative valuations for cable and satellite is essentially the same. That is, there is no reason to believe and no evidence to suggest that SOs value programming differently than CSOs to any noticeable degree based on the available data, and there is strong reason to expect that SOs and CSOs value programming similarly, as would be expected of direct competitors in the same market.") and Erdem Amended Satellite WDT, ¶ 82, ("As I argue in this report, there are no apparent reasons why category valuations should differ markedly between the cable and satellite proceedings.")

.3 Erdem Amended Satellite WDT, ¶ 51. ("As summarized above in this report, I criticized the use of regression analysis in the cable proceeding for a number of reasons. I conclude that the criticisms apply equally to the satellite proceeding, making regression analysis an unreliable approach to estimate relative market value of programming.")

4 Erdem Amended Satellite WDT, ¶ 53. ("But because I need to start with some specification in order to illustrate more clearly why a hedonic regression is not expected to reveal value in these proceedings, I decided to start by trying to adapt Dr. Crawford's regression in the cable proceedings for use with satellite retransmission data.")

5 Corrected Testimony of Randal D. Heeb, Ph.D. In re Distribution of Satellite Royalty Funds, No. 14-CRB-0011-SD (2010-13) (filed March 22, 2019, corrected June 7, 2019) (hereinafter "Heeb CWDT"), ¶ 10.

6 Crawford CWDT, ¶ 125. ("Estimating our key parameters of interest therefore requires variation *within systems* and *across time*. Fortunately, the subscriber group reporting introduced with STELA and the availability of four years of data allows the model to rely on just this sort of variation. Subscriber group reporting ensures that systems report, for each subscriber group, the distant broadcast signals carried in that subscriber group, and thus one can calculate the minutes of alternative programming types carried in that subscriber group. Relating the variation in those programming minutes with the variation in subscriber group–level royalties helps identify our key parameters of interest.")

7 The detail available in the satellite data is limited to the number of subscribers for each station, which is not sufficient to implement the Crawford regression model. *See* Heeb CWDT, ¶ 10 ("In the satellite context, data limitations prevent a

Fortunately, since Dr. Erdem and I agree that the relative values of claimant group minutes are likely very similar in both contexts, the estimated cable regression coefficients can be applied directly to the satellite minutes to inform the royalty allocations in the satellite context.

II.B. Dr. Erdem's criticisms of the cable regression results of Dr. Crawford

(18) Dr. Erdem criticized Dr. Crawford's regression specification in his testimony in the cable matter, and repeated much of that criticism in his testimony in this matter.[8] Dr. Erdem does so in support of his argument that the estimates of relative value obtained from Dr. Crawford's regression analysis in the cable case should not be used in this proceeding. To be clear, since Dr. Erdem and I agree that the true relative valuations are very similar in the two contexts, the question is not whether the relative valuations of claimant group minutes in the cable context can be used in the satellite context—we agree that the relative valuations are likely very similar. Rather, the question posed by Dr. Erdem is whether the estimates obtained in the cable context were and are reasonable estimates of the true relative valuations. If they are, then it follows that they are also reasonable choices for me to apply as estimates of the very similar relative valuations in the satellite context.

(19) For the purposes of my rebuttal testimony, I will assume that this is not a settled question, and I will review and assess the arguments regarding whether the cable regression coefficients are valid measures of the relative values of claimant programming minutes and therefore appropriate to apply to calculate satellite royalty shares.

II.B.1. The fixed effects specification exploits characteristics of the cable data that are absent in the satellite data

(20) In his testimony in this matter, Dr. Erdem criticizes Dr. Crawford's focus on variation within a system and accounting period to identify the relative values of claimant minutes, stating: "[I]t is not clear to me *why* we would be interested in variation within a system and accounting period, rather than across systems or accounting periods."[9] I have examined Dr. Crawford's explanation for this modeling

direct application of Dr. Crawford's methodology. Obtaining satellite-specific regression coefficients on minutes directly from satellite data is infeasible for at least two reasons. First, unlike the cable context, in which multisystem cable operators report distant signal royalties by subscriber group, satellite carriers provide distant signal royalty data by station on a national level.")

[8] *See* Erdem Cable Testimony, pp. 13–14. ("The starting point for the regression models presented by Dr. Israel, Dr. Crawford, and Dr. George is the approach that was presented by Dr. Waldfogel in the 2004–2005 proceedings. I will refer to this models as "Waldfogel–type regressions in the rest of my testimony. . . . There are many reasons why Waldfogel-type regressions do not measure relative markets value.")

[9] *See* Erdem Amended Satellite WDT, ¶ 67. ("I implement this regression analysis at the station level, the most detailed level that is available, which I believe is the approach most consistent with Dr. Crawford's apparent intent to apply his approach to the most detailed level available so as to permit the use of fixed effects at the system-accounting period level, thereby observing variation within a system in an accounting period, rather than across systems or accounting

choice, as expressed in his testimony in the cable proceeding.[10] Essentially, by focusing on within-system, within-period variation, Dr. Crawford exploited differences across different subscriber groups to identify the effect of different claimant group minutes on royalties, while controlling for the possibility of confounding but unobserved time- and system-level differences using his "fixed effects" model. This fixed effects modeling approach is commonly used by economists to control for potentially confounding effects across modeling dimensions and over time.[11] It was appropriately cited by the Judges in their Final Determination, which explicitly pointed out the advantages of this feature of Dr. Crawford's specification.[12]

(21) Dr. Erdem's criticism of this technique, which is made in the context of his satellite regression, is that Dr. Crawford could instead have used across-system and across-time variation. This criticism is invalid for several reasons. While such across-system and across-time variation might be useful, it would require that the econometrician explicitly control for all the myriad and often unobservable factors specific to the system or the time period that could cause variation in the royalties or claimant minutes. Dr. Crawford's model, with time and system fixed effects, eliminated the need for such explicit control variables.

(22) More importantly, Dr. Erdem makes this criticism of Dr. Crawford's regression specification in the context of Dr. Erdem's satellite regression, which is applied to data that do not have the subscriber-group dimension. That critical characteristic of the cable data made it possible to compare royalties attributable to different subscriber groups within a system and accounting period—where all subscribers within a subscriber group observation shared a complement of distant signals, system, and time. The system and time dimension characteristics were controlled for using the fixed effects

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periods. It is not clear to me *why* we would be interested in variation within a system and accounting period, rather than across systems or accounting periods.")

10 *See* Crawford Corrected Cable Testimony, ¶ 107. ("I also include dummy variables/or each cable system in each accounting period in the data. This is called a "fixed effect" in econometrics (in this context, a "cable system-accounting period fixed effect"), as it allows for any feature that influences the royalty paid by that cable system in that accounting period to be flexibly estimated from the data, leaving variation in the royalty paid across subscriber groups within each cable system and across time within those subscriber groups to identify the effect of changes in minutes of each programming type on royalties.")

11 *See*, e.g., William H. Greene, *Econometric Analysis*, 2nd ed. (New York: Macmillan, 1993), 466, for a formal definition of a fixed effects regression model; *also see*, e.g., Joshua D. Angrist and Jörn–Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton, NJ: Princeton University Press, 2009), 222–25, for some prominent examples from the economics literature which demonstrate how this model is implemented in practice.

12 *See* Final Determination of Distribution of Cable Royalty Funds, In re Distribution of Cable Royalty Funds, No. 14-CRB-0010-CD (2010–13), 84 Fed. Reg. 3553. [hereinafter "CRB Final Determination"], 36–37. ("Not only did Professor Crawford sufficiently respond to the criticisms of his regression analysis, that analysis is based on a number of other factors as to which no criticisms were leveled. First, he used the universe of all programming on all distant signals, rather than a sampling, thus avoiding problems that may be associated by sampling or inadequately sized samples. Second, by using data and royalties at the subscriber group level, his regression analysis related more specifically to programs and signals actually available to subscribers and provided more variation and observations than past regressions. Third, his use of a fixed effects approach avoided the criticism that he had omitted key variables.")

model, allowing the econometrician to isolate the relevant differences in the claimant minutes available to that group and to estimate their relationship to royalties.

(23) The absence of this subscriber-group dimension in the satellite data makes it impossible to implement Dr. Crawford's fixed effects regression methodology in the satellite context. In fairness to Dr. Erdem, his purpose in attempting the satellite regression was to demonstrate that it does not work. I agree that one cannot implement Dr. Crawford's regression in the satellite context. However, Dr. Erdem errs in inferring from this failure, which is a failure of the data in the satellite context to meet the requirements of the Crawford model, that there is some analogous deficiency in Dr. Crawford's cable regression. The cable data are not deficient in this way. The Crawford model was designed for the cable context precisely to exploit the particular structure of those data. In my opinion, that model did exactly what it was intended to do, which is to exploit variation at the subscriber-group level (within system and time period) in order to isolate the effects of different distant signal carriage choices, and their associated claimant minute differences.

II.B.2. Controlling for system size using the lagged number of subscribers

(24) Dr. Erdem repeats his criticism of Dr. Crawford's regression, debated at length in the cable proceeding, that the regression should not have included as a control for the system size the (lagged) number of subscribers in the subscriber group, interacted with the identity of the MSO which owns the system.[13] Dr. Erdem states:

> I must pause to say here that the purpose of a control for the level number of subscribers in Dr. Crawford's regression in the cable proceeding is entirely unclear to me. It necessarily introduces a substantial bias in the results, as it introduces a relationship that is clearly inconsistent with the known relationship between subscribers and fees paid. Therefore, the level number of subscribers cannot possibly remove the influence of the number of subscribers on the dependent variable, which is the purpose of having a control variable.[14]

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[13] *See* CRB Final Determination, 24–25. ("The SDC's expert, Dr. Erkan Erdem, testified that Professor Crawford's use of the linear form for this control variable was improper, because it failed to correspond with the actual relationship between royalty fees and subscribers. As a consequence, Dr. Erdem maintained, Professor Crawford had introduced statistical 'bias' into his regression. . . . In response, CTV and Professor Crawford argued that Dr. Erdem misapplied a principle that might be valid in a '*prediction*' regression. Professor Crawford maintained though that his own regression on behalf of CTV was an '*effects*' regression, seeking to explain the issue at hand, i.e., how different program categories correlate with the royalties paid.")

[14] *See* Erdem Amended Satellite WDT, ¶ 73. Note that the control that Dr. Crawford implements is the lag number of subscribers.

(25) Dr. Erdem made a similar assertion during the cable case.[15] Dr. Crawford explained his rationale of the lag of the number of subscribers in his testimony.[16] In the cable case, the Judges in their Final Determination considered this point and explained at length the advantages of Dr. Crawford's inclusion of the lag number of subscribers.[17]

(26) I have examined the record of this debate in the cable proceeding. Like Dr. Crawford, I note that there may be systematic differences between larger and smaller systems that impact the value of distant signals (and their component claimant minutes) to those systems, and that including a variable to control for system size is an appropriate means of addressing this potentially confounding factor. Dr. Crawford's choice of the lagged number of subscribers interacted with MSO identity does control for such differences.

(27) Dr. Erdem has provided no additional or new rationale for restating his assertion. Moreover, Dr. Erdem further obfuscates the issue by reintroducing the previously discredited idea of using the lagged log of the number of subscribers as an alternative to Dr. Crawford's specification.[18] I address this error by Dr. Erdem separately in section II.E.

(28) However, Dr. Erdem does make one observation that may be of assistance in resolving the debate. Namely, Dr. Erdem suggests evaluating the Crawford regression without that variable.[19] One could drop that variable from the regression and avoid the ensuing controversy, but at the cost of losing the necessary control for system and subscriber-group size. I do not recommend such a change. However,

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15 *See* Rebuttal Testimony of Erkan Erdem, Ph.D. In re Distribution of Cable Royalty Funds, No. 14-CRB-0010-CD (2010-13) (filed September 15, 2017) (hereinafter "Erdem Rebuttal Testimony"), 16 at ¶ 2. ("Next, I evaluated the change in the resulting shares from using a log–transformation of the lagged number of subscribers variable, instead of using the untransformed variable. The transformation is motivated by the fact that royalties depend on gross revenue, which in turn depends in larger part on the number of subscribers. Dr. Crawford's log–transformation of royalty fees is therefore inconsistent with his decision not to transform the closely correlated variable of lagged number of subscribers. Log transforming the number of the lagged number of subscribers is more internally consistent with the transformation Dr. Crawford applied to the dependent variable, royalty fees.")

16 *See* Crawford Corrected Cable Testimony, ¶ 118. ("These include variables that shift demand across markets (number of local stations, number of activated channels), variables that dictate whether any of the special fees associated with distant signals royalties were paid (the 3.75% fee, the syndicated exclusivity surcharge, and the number of permitted stations), variables to control for the size of different systems (lagged subscribers interacted with the identity of the MSO which owns the system), and a variable to ensure the econometric model reflects the realities of distant signal carriage (the number of distant stations).")

17 *See* CRB Final Determination, 24. ("The Judges find that Professor Crawford's regression is not compromised by his use of the linear form to express the number of subscribers in this control variable…Professor's Crawford's use of a linear form for the number of subscribers served to control for the size of the system without overriding the purpose of the regression, which was to measure the effects (if any) of different program categories on royalties paid.")

18 *See* Erdem Amended Satellite WDT, ¶ 122. (Referring to a subset of his sensitivity tests Dr. Erdem states: "Models 6–11 are estimated similarly to Models 0–5, except that the log of lagged subscribers is used rather than the level of lagged subscribers.")

19 *See* Erdem Amended Satellite WDT, ¶ 73. ("[I]f Dr. Crawford's purpose was to "control" for the effect of subscribers on fees paid, he should have used the natural logarithm of the distant subscribers. On the other hand, if his theory was based on a proposed relationship between fees paid and value (implicit in his response that a control for the logged number of subscribers merely "replicates" the formula for calculation of fees), then he should not have controlled for the number of subscribers at all.")

I examined Dr. Erdem's proposed model by taking the computer code from his backup materials and modifying his baseline regression by removing the control for the number of subscribers in the subscriber group. The changes in the implied shares of distant signal satellite royalties are small.[20]

(29) This does not imply that it is appropriate to drop that variable from the regression. It is still required to control for system size. However, this exercise does give some comfort, with respect to Dr. Erdem's concerns that the Crawford regression is somehow "ill-suited to measure accurately"[21] the relative value of claimant minutes, that the results of this alternative regression are not so different as to suggest that the results from the proper model are driven substantially by this one control variable.

II.B.3. Dr. Erdem's criticisms regarding the "absolute" verses "relative" interpretation of the regression coefficients are invalid

(30) In his Initial Testimony in this matter, Dr. Erdem suggests that Dr. Crawford's treatment of the regression coefficient on each claimant's programming minutes implies that Dr. Crawford interpreted the coefficients as representing absolute values. For instance, Dr. Erdem writes:

> To estimate an absolute effect, which is how Dr. Crawford seems to have treated his explanatory variables by assuming that the effect is equivalent to a measure of marginal value [. . . .][22]

(31) While Dr. Erdem is correct in describing Dr. Crawford's regression coefficients on claimant minutes as representing marginal values, Dr. Erdem never explains why he believes that marginal values in turn must represent absolute values, rather than values relative to off-air and network minutes. Indeed, I have reviewed Dr. Crawford's explanation of his interpretation of the coefficients on claimant minutes as *relative* values, and Dr. Crawford specifically explained that the coefficients represent the value of a minute of claimant programming *relative* to a minute of off-air and network.[23]

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[20] The shares of Program Suppliers, CTV, and Devotional go down by 1.44%, 1.65%, and 0.06% respectively, and the share of JSC goes up by 3.14%.

[21] *See* Erdem Amended Satellite WDT, ¶ 73. I also disagree with Dr. Erdem's characterization of Dr. Crawford's model as "intended to measure a correlation between subscribers and minutes," but this error is not relevant to his criticism or to my argument that his criticism is itself incorrect.

[22] *See* Erdem Amended Satellite WDT, fn. 58. ("To estimate an absolute effect, which is how Dr. Crawford seems to have treated his explanatory variables by assuming that the effect is equivalent to a measure of marginal value, one would have needed to include a variable for each category and to exclude the variables (like number of distantly retransmitted stations and total number of unduplicated minutes) that are closely related to the total number of minutes in all categories. This is the basic error that I acknowledged with respect to some of my sensitivity tests presented in the cable proceeding, and that infected both of Dr. Crawford's specifications in exactly the same way.") (*Also see*, e.g., Erdem Amended Satellite WDT, ¶¶ 74, 94.)

[23] *See* Crawford Corrected Cable Testimony, ¶ 119. ("[T]he inclusion of the number of distant stations as a covariate is particularly important as it means the regression coefficients on the programming minutes of each programming type can be interpreted as the impact on royalties of an increase in the programming minutes of that type, taking away a minute of non-compensable network programming (e.g., Big-3 network programming), or off-air programming. This specification also allows, for example, Big-3 network programming to have value to cable operators but then measures

(32) In addition, as a practical matter, in the calculation of the royalty shares using those coefficients, only the relative value of each coefficient, relative to all the other coefficients, matters. Because the claimant shares of the royalty pool must, by construction, add up to 100%, only the relative size of each coefficient compared to the sum of all the others matters for the ultimate royalty distribution. If all the coefficients were rescaled by a common multiple, for example, the resulting royalty shares would be unchanged. (This is the same reason that royalty shares can be calculated in the satellite context using coefficients from the cable context even though the original cable regression had more claimant groups, and correspondingly more coefficients on claimant group minutes, than there are in the satellite context.)

(33) In his response to my direct testimony, Dr. Erdem claims that I too attributed an absolute interpretation to Dr. Crawford's regression coefficients.[24] On the contrary, I have always interpreted those coefficients as representing relative values. I believe that this understanding is consistently reflected in my testimony.[25]

(34) While ignoring Dr. Crawford's explicit descriptions of the coefficients as measuring relative values, Dr. Erdem in his Initial Testimony proceeds to offer the same relative interpretation himself:

> Thus, whether or not it was his intent, the coefficients for the categories of minutes in Dr. Crawford's analysis [. . .] should be interpreted as the "effect" [. . .] of an additional minute of that category's programming *relative to* the "effect" of an additional (combined) minute of off-air and network programming.[26]

(35) Dr. Erdem, Dr. Crawford and I all appear to agree that the coefficients on claimant group minutes from Dr. Crawford's cable regression analysis reflect the relative value of an additional minute of that claimant group time, and they further agree that relative value of claimant group minutes is the primary object of interest for calculating royalty shares. In addition, the Judges, in the cable proceeding, concurred with this interpretation, noting that the relative value is all that matters for the reasonable determination of royalty allocation shares.[27] Despite this, Dr. Erdem proceeds in a futile

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the value of other categories of programming relative to the value of such programming, at least in my initial regression results.") *See also* Allocation Hearing Transcript of Gregory S. Crawford. Volume VII, Feb. 28, 2018 (hereinafter "Cable Hearing Transcript, day 7") 1569.. (*See also*, e.g., CRB Final Determination, 25).

[24] *See* Erdem Amended Satellite WDT, ¶ 110. ("Models 1 and 2 attempt to answer Question #1 related to Dr. Crawford's incorrect use of a specification that measures coefficients for category minutes relative to the coefficient for network and off-air minutes, rather than the absolute effect that Dr. Crawford and Dr. Heeb seem to attribute to them.")

[25] *See* Heeb CWDT, ¶ 11. ("I import only the beta coefficients that reflect the relative value of distant signal minutes from the cable context; all other information I use to calculate the appropriate shares of the satellite distant signal royalty by claimant category is satellite specific. "). *See* also, Heeb CWDT at ¶¶ 12, 15, 17.

[26] *See* Erdem Amended Satellite WDT, ¶ 75.

[27] *See* CRB Final Determination, footnote 17. ("In this proceeding, the Judges distinguish between "relative values" (to describe the allocation shares), and absolute "fair market values." Because the royalties at issue in this proceeding are regulated and not derived from any actual market transactions, they do not correspond with absolute dollar royalties that would be generated in a market and thus would not reflect absolute "fair market value.")

attempt to recover a measure of absolute value of the contributed minutes. I discuss his attempt in section II.C.

II.C. Dr. Erdem does not provide a measure of absolute value of claimant minutes

(36) In his Amended Testimony, Dr. Erdem seems to reverse his characterization from his original (satellite) direct testimony, providing citations from Dr. Crawford's testimony where Dr. Crawford made explicit the point that the regression coefficients on claimant minutes represent relative values.[28] Yet in this same Amended Testimony, Dr. Erdem performs an exercise in which he claims to calculate absolute values of each claimant category minute.

(37) Dr. Erdem attempts to demonstrate that Dr. Crawford's regression is misspecified, [29] and purports to calculate the absolute value of claimant minutes by adding to each of Dr. Crawford's claimant minute regression coefficients a constant equal to the coefficient on the number of distant signals divided by 262,800.[30] However, Dr. Erdem's calculation, which he puts forth in his Model 1, does not generate absolute values of claimant minutes. Furthermore, the fact that some of Dr. Erdem's calculated values are negative does not in any way suggest that Dr. Crawford's specification is nonsensical.[31]

(38) Dr. Erdem motivates his calculation as follows:

> Adding a signal to a subscriber group comes with a certain number of additional minutes for each program category, and we have a coefficient for the effect of each minute of content on log of royalties paid. For any given category, the effect of another minute of programming due to the additional distant signal is equal to the

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28 *See* Crawford Corrected Cable Testimony, ¶¶ 5, 44, 46, 55, 69–70, 91, 119. (At CWDT ¶¶ 90–91: "In this section I present the econometric framework that I believe is best suited to determine the appropriate division of royalty payments for programming carried on distant broadcast signals imported on cable television systems between 2010 and 2013. There are two parts to this framework. First, I specify and estimate an econometric model that can recover the relative value to cable operators of minutes of alternative programming and other control variables within each subscriber group and accounting period. This provides estimates of the marginal value of different types of programming content.")

29 "Question 1: What is the impact of Dr. Crawford's misspecification by including number of distant signals as a covariate, and excluding network minutes?" (Erdem Amended Satellite WDT, § IX.A.1.)

30 *See* Erdem Amended Satellite WDT, ¶¶ 110, 112. (At ¶ 110: "Models 1 and 2 attempt to answer Question #1 related to Dr. Crawford's incorrect use of a specification that measures coefficients for category minutes relative to the coefficient for network and off-air minutes than the absolute effect that Dr. Crawford and Dr. Heeb seem to attribute to them." At ¶ 112: "Model 1 takes the baseline regression coefficients from Model 0 and adds a "per minute" effect of an additional distant signal (i.e., the coefficient for distant signals, which is the effect of having one more distant signal on the dependent variable, divided by 262, 800 minutes in an accounting period) to each of the claimant category coefficients.")

31 *See* Erdem Amended Satellite WDT, ¶ 115. ("It is worth noting that the Judges discussed the presence of negative coefficients in their Final Determination and did not find the presence of negative coefficients to be "nonsensical" in the context of *relative* effects. However, because these coefficients should be interpreted as *absolute* effects, the negative coefficients should be viewed as nonsensical, in my opinion, for the reasons stated earlier in this paragraph.")

> effect of the additional minute of programming for that specific category plus the "overall" effect of an additional minute regardless of the program category. Without such a level shift, the regression fails to account for the effect of network and off-air programming, and measures other category coefficients relative to the implied coefficient of network and off-air programming.[32]

(39) However, Dr. Erdem is incorrect to interpret the coefficient on the number of distant signals as the value of network programming and off-air programming. Dr. Crawford testified as to the interpretation of the number of distant signals variable.[33] I agree that Dr. Crawford's interpretation is appropriate. This coefficient is included in the regression specification to ensure that the coefficients on the claimant minutes can be interpreted as relative values by effectively imposing that the number of total minutes of programming does not change when contemplating the value of an additional claimant minute. I have also reviewed Dr. Crawford's explanation of why that coefficient has a negative value.[34] He explains that the fact that it is negative is due to a particular feature of the distant signal equivalent (DSE) structure and does not suggest that network programming somehow has a negative value. Rather, it is an artifact of the cable royalty structure, in which some distant signals (network stations) have a royalty that is only one-quarter as much as other stations' royalties (independent stations).

(40) Dr. Erdem's exercise of adding the rescaled number of stations coefficient to the relative value of a claimant minute does not yield absolute values of claimant minutes. In my opinion, the resulting value has no logical interpretation.

(41) Dr. Erdem then performs a second exercise, which he describes as a regression-based method of performing a similar calculation, which he puts forth as his Model 2. Dr. Erdem claims that his Model

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32 *See* Erdem Amended Satellite WDT, ¶ 113.

33 *See* Crawford Corrected Cable Testimony, ¶ 119. ("[T]he inclusion of the number of distant stations as a covariate is particularly important as it means the regression coefficients on the programming minutes of each programming type can be interpreted as the impact on royalties of an increase in the programming minutes of that type, *taking away a minute* of non-compensable network programming (e.g., Big-3 network programming), or off–air programming. This specification also allows, for example, Big–3 network programming to have value to cable operators but then measures the value of other categories of programming *relative* to the value of such programming, at least in my initial regression results.")

34 *See* Cable Hearing Transcript, day 7, 1606. As Dr. Crawford explained:

> [T]o understand that coefficient is to imagine two environments, one where there is an independent station with a particular portfolio of the minutes of the -- of the six programming categories, and suppose that they have -- all the minutes were of the six program categories.
>
> And then imagine another equivalent subscriber group that had two network stations with half of its -- each network station had half of the total minutes of the six categories, so that the total across the two stations would be equal to the total minutes of the independent station.
>
> And then, of course, the other half would be network programming, non-compensable network programming. But because network stations are -- only pay royalties of .25 DSE, the royalty would be only at the .5 DSE level compared to the full DSE for the independent station.
>
> And so basically this says that this number of distant signals is capturing the fact that the DSE payment is lower for the -- for these network stations. (Cable Hearing Transcript, day 7, 1604–05).

1 and his Model 2 are effectively performing the same exercise.[35] However, doing the same experiment twice and getting the same answer does not fix the fundamental problem with the experiment. Neither version recovers Dr. Erdem's so-called absolute value. The first transforms the coefficients by adding a value that is not simply a component part of the absolute claimant coefficient. The second version re-estimates the regression without the necessary control to ensure that total minutes are held constant. The fact that both models yield very similar results does not provide any insight into the relative values of claimant minutes, which Dr. Crawford reports (and which are closely replicated in Dr. Erdem's Model 0) and which are the subject of interest in the royalty distribution proceedings. I cannot identify any insights whatsoever regarding Dr. Crawford's cable regressions that can be drawn from this experiment, and certainly not those that Dr. Erdem claims to obtain.[36]

II.D. Dr. Erdem's adjustment for satellite's different rules regarding compensability is unnecessary and unreliable

(42) Dr. Erdem correctly points out that "[n]etwork programming is treated as non-compensable in the cable proceeding, but it must be treated as compensable in the satellite proceeding."[37]

(43) Dr. Erdem then asks "how the treatment of network minutes as non-compensable (vs. compensable) affects the cable regression results."[38] The answer to this question is straightforward: rules about compensability do not affect the estimate of the coefficients in the cable case at all. Dr. Crawford's regression in the cable case uses total minutes, not compensable minutes, as the basis of the coefficient estimation. Dr. Crawford explained this point in his testimony in the cable proceeding.[39]

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35 *See* Erdem Amended Satellite WDT, ¶ 118: ("Model 2 estimates a regression similar to the baseline regression, except that I omit the variable for the number of distant signals, but add variables for network and off–air minutes. The rationale for this model is that by including all programming types (of minutes), I still effectively hold the total minutes of distant programming as fixed, as Dr. Crawford claimed was his purpose for including a variable for the number of distant signals. However, because I include the variables for network minutes and off–air minutes instead of a variable for the number of distant signals, the results can be interpreted as an *absolute* effect, rather than being relative to network and off–air minutes. As expected, the coefficients and implied shares for Model 1 and Model 2 are nearly identical.")

36 *See* Erdem Amended Satellite WDT, ¶¶ 118, 129–133. (¶ 131: "In addition to my general criticism of Dr. Crawford's regression approach, the fact that many of the sensitivity regressions include negative coefficients—most notably Models 1 and 2, which are the same as Dr. Crawford's baseline model, except with the correct consideration of network programming—shows that Dr. Crawford's model cannot be relied upon as a measure of value, based on the Judges' criteria in their Final Determination for the 2010–2013 cable proceeding.")

37 *See* Erdem Amended Satellite WDT, ¶ 104. ("Network programming is treated as non–compensable in the cable proceeding, but it must be treated as compensable in the satellite proceeding.")

38 *See* Erdem Amended Satellite WDT, ¶ 104. ("The purpose of this question is to investigate how the treatment of network minutes as non-compensable (vs. compensable) affects the cable regression results. This matters given that Dr. Heeb relies on coefficients from Dr. Crawford's analysis with the cable data in his testimony for the satellite stage of this proceeding, and the treatment of network minutes should clearly be different for a satellite allocation in which network programming is compensable.")

39 *See* Cable Hearing Transcript, day 7, 1402. ("Q. We have had discussions in this proceeding of compensable programming. Do these average marginal values in Figure 16 measure all the value of all the programming on the

Cable system operators (CSOs) maximize profit by choosing different bundles of distant signal stations. From the CSOs' perspective, it is irrelevant whether programming content is compensable to the rights-holders.

(44) In response to my direct testimony, Dr. Erdem states: "Dr. Heeb relies on coefficients from Dr. Crawford's analysis with the cable data in his testimony for the satellite stage of this proceeding, and the treatment of network minutes should clearly be different for a satellite allocation in which network programming is compensable."[40] To the extent that Dr. Erdem means that the satellite royalty allocation should be calculated using the compensable minutes from the satellite context, applied to the coefficients estimated by the cable regression, he is correct. That is the calculation that I performed when calculating the satellite royalty allocation. However, Dr. Erdem also seems to imply that compensability (or the difference in compensability between the satellite and cable contexts) should somehow affect the estimation of the coefficients from Dr. Crawford's cable regression.[41] If that is Dr. Erdem's meaning, then he is incorrect. I have reviewed Dr. Crawford's testimony on this subject.[42] Compensability does not enter into the question of estimation of the regression coefficients at all in Dr. Crawford's cable regression. Moreover, in my opinion, Dr. Crawford's treatment with respect to compensability is correct.

(45) Moreover, the differences in compensability between the cable and satellite contexts do not matter at all, because compensability does not matter to correctly estimate coefficients in the cable context, and

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distant signals or just the compensable programming? A. All the programming. Q. Why did you design the study in that way? A. Because CSOs are choosing entire distant signals and, presumably, value—aren't aware or care, even, about the mix between compensable and non-compensable programming.")

40 *See* Erdem Amended Satellite WDT, ¶ 104. ("This matters given that Dr. Heeb relies on coefficients from Dr. Crawford's analysis with the cable data in his testimony for the satellite stage of this proceeding, and the treatment of network minutes should clearly be different for a satellite allocation in which network programming is compensable.")

41 *See* Erdem Amended Satellite WDT, ¶ 104. ("Network programming is treated as non-compensable in the cable proceeding, but it must be treated as compensable in the satellite proceeding. Hence, the purpose of this question is to investigate how the treatment of network minutes as non-compensable (vs. compensable) affects the cable regression results.")

42 *See* Crawford Corrected Cable Testimony, ¶¶ 143–144 ("As shown in Section V.C.2.b, there is substantial duplication in the programming carried on distant broadcast stations due to network affiliation of multiple stations with the same network. In the initial regression analysis, the results of which I presented above, I ignored this duplication of programming and any effects it might have on either the regression results or share calculations. In this subsection, I consider the issue in greater detail…I re–estimated my econometric model imposing that *all duplicated network programming has zero value to cable systems*. . . Because non–Big–3 network programming is compensable, and because this process meant that I dropped some compensable programming in this supplementary analysis, it is important to understand that by doing so I am still appropriately valuing all compensable programming. The intuition behind this conclusion is as follows. If I am correct in assuming that duplicate network programming has zero value to cable systems, then including such minutes in the initial econometric estimates means the model is necessarily estimating an *average* value for programming minutes of each programming type, with the average taken across non–duplicate programming (that has positive value) and duplicate programming (that has zero value). By dropping programming that has zero value, I am *deaveraging*: I am attributing the full value of the positive non-duplicate programming just to the non-duplicate programming (and the zero value of the duplicate programming to the duplicate programming). The value lost by dropping the duplicative compensable programming is made up by multiplying the remaining compensable programming by the (higher) deaveraged value per minute.") Figures 18, 19, 20 at Crawford Corrected Cable Testimony, 44–46, report Dr. Crawford's regression results for the non-duplicates analysis.

because the true relative values estimated by those coefficients are approximately the same in the cable context as in the satellite context (as Dr. Erdem and I agree). Only the allocation share calculations, which in both cases reflect the cable coefficients combined with the compensable minutes in the respective cable or satellite context, are affected by the difference in compensability.[43]

(46) In his investigation of his hypothesized effects of compensability on cable regression coefficients, Dr. Erdem estimates alternative cable coefficients by reallocating network minutes to claimant categories and estimating a new regression. However, Dr. Erdem's new regression model is badly misspecified and generates uninterpretable results. This is because of a well-known technical econometric concern called multicollinearity, which arises when one or more regressors are (or nearly are) linear combinations of other regressors.[44]

(47) The problem with Dr. Erdem's modified regression that causes multicollinearity is that once he has reallocated network minutes from the omitted category, only off-air minutes remain in that category. Because off-air minutes are a tiny fraction of all minutes (0.34%), the sum of all of the claimant minutes in any subscriber group almost exactly equals the total of the minutes in the period times the number of distant stations for that subscriber group.[45] The result is that when Dr. Erdem runs his modified regression, the claimant minutes regressors are almost perfectly correlated with the number of distant stations (because the number of stations times the number of minutes in the period equals the sum of all the claimant minutes, plus the off-air minutes.)[46] The result is that the coefficients on claimant minutes become (nearly) unidentified, can vary wildly from their true values, and hence become uninterpretable. This is not because of any inherent deficiency in the data or in Dr. Crawford's more reliable model, but because of the modeling error introduced by Dr. Erdem's revised regression specifications.[47] Dr. Erdem's Model 3 is irredeemably flawed because of

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[43] More precisely, Dr. Crawford and I both excluded the appropriate non-compensable minutes in our respective share calculations. Since the network programming and WGNA's national feed are not compensable in the cable proceeding, Dr. Crawford did not include those in his share calculations. Since in the satellite context network programming is compensable but the WGNA national feed is not, I only exclude the WGNA national feed from my share calculations. *See* Heeb CWDT, Figure 10, p. C–5.

[44] *See* William H. Greene, *Econometric Analysis*, 2nd ed. (New York: Macmillan, 1993), 266, defines a multicollinearity problem as one in which "the measured variables are too highly intercorrelated to allow precise analysis of their individual effects." Dr. Rubinfeld also offered a related opinion on the multicollinearity problem that is also consistent with my assessment of Dr. Erdem's experiments. *See* Written Direct Testimony of Daniel L. Rubinfeld, In re Distribution of Satellite Royalty Funds, No. 14-CRB-0011-SD (2010-13) (filed March 22, 2019, amended June 7, 2019) (hereinafter "Rubinfeld Amended WDT"), ¶ 28. ("If one or more covariates are highly correlated with the covariate whose parameter is of particular interest, it may be difficult to determine the relationship between the covariate at issue and the dependent variable with accuracy. High standard errors associated with the measurement of the coefficient on the covariate at issue can be a sign of possible *multicollinearity*.")

[45] Erdem Amended Satellite WDT, electronic backup.

[46] The R-squared statistic from a regression of the number of distant stations on all the other regressors in Dr. Erdem's specification is 99.85%, a clear indicator of multicollinearity.

[47] Dr. Erdem purports to study the effects of differences in compensability between the cable and satellite context with three sensitivity models discussed. *See* Erdem Amended Satellite WDT, ¶¶ 119–21, 129–33. This is the discussion of his "Question #2." (At ¶ 119: "Models 3–5 are similar to Models 0–2, except that in an attempt to answer Question #2 above, I redistribute network minutes to the corresponding non-network category in the underlying regression data.")

multicollinearity. His Models 4 and 5, which are permutations of the flawed experiment that I described in section II.C., suffer from the same problem. Hence, in my opinion, those experiments also do not demonstrate any problem either with the cable data or Dr. Crawford's cable regression model.

II.E. Dr. Erdem's regression model with the log of lagged subscribers as a covariate closely replicates the royalty formula and does not estimate the relative value of claimant minutes

(48) In his Amended Testimony, Dr. Erdem criticizes my use of the cable coefficients by reintroducing the argument that he made in the cable proceedings, asserting that Dr. Crawford's regression introduces bias because it specifies the relationship between royalties and subscribers by using a linear term of the lagged subscribers.[48] I addressed this criticism in section II.B.2. He goes further, also repeating arguments made and rejected in the cable proceeding, that Dr. Crawford's regression should instead have included the log of lagged subscribers.[49] Alternatively, he argues that the difference between Crawford regression results and Dr. Erdem's respecification, which includes the log of lagged subscribers, is evidence of an inherent instability in the Crawford regression.[50] Here, I address this critique as it applies to my opinion that it is appropriate to use the cable regression coefficients to calculate the satellite allocation.

(49) It is very clear that in Dr. Erdem's revised regression, the log of lagged subscribers explains nearly all the variation in the log of royalties, leaving nothing left to be explained by any other variable, including the coefficients of interest relating claimant group minutes to royalties.[51] This exercise defeats the purpose of determining the relative contributions of different claimant groups. An estimation procedure that includes the log of the number of subscribers, lagged or unlagged, results in a near mechanic replication of the log of the royalty formula. But we already know the royalty formula. If we wanted to predict royalties, we could simply apply that formula, without any

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[48] *See* Erdem Amended Satellite WDT, ¶¶ 69, 73-74, 87, 94, 105, 122. (*Also see,* e.g., Cable Hearing Transcript Day 1, 15–16.)

[49] *See* Erdem Amended Satellite WDT, ¶ 73, 87, 94, 122–25. (At Erdem Amended Satellite WDT, 32, Dr. Erdem states, "Question #3: What is the effect of misspecification—relating the log of royalties to the level of subscribers—on Dr. Crawford's regression results?" At Erdem Amended Satellite WDT, ¶122: "Models 6–11 are estimated similarly to Models 0–5, except that the log of lagged subscribers is used rather than the level of lagged subscribers. This helps answer Question #3 above, by allowing the model to accurately reflect the relationship between royalties and subscribers (as opposed to Dr. Crawford's model, which introduces distortion by incorrectly specifying the relationship between royalties and subscribers).")

[50] *See* Erdem Amended Satellite WDT, ¶ 125. ("These results show that the regressions do not provide a reliable measure of value, and that there is no meaningful relationship between the number of minutes of programming and fees paid. Once again, these sensitivities reveal the flaws in Dr. Crawford's model and in fee-based regressions generally.")

[51] Dr. Erdem concedes as much in his testimony. *See* Erdem Amended Satellite WDT, ¶ 87. ("Given that there is a direct relationship between the number of subscribers and royalty payments, this creates an almost perfect relationship (R-squared of 0.94) between the dependent variable (natural logarithm of royalty amount) and the natural logarithm of the number of subscribers making all other coefficients statistically insignificant.")

regressions. Our purpose is instead to *estimate* the relative contributions of different claimant groups.[52]

(50) As an example of the problem with Dr. Erdem's recommendation, imagine an executive who is trying to understand the factors driving the profit of her company. Dr. Crawford's regression is analogous to explaining profit by a regression that includes various factors that might affect said profit, such as cost of capital, customer feedback, marketing efficacy, R&D expenditure and market penetration, etc. Dr. Erdem's methodology, however, is akin to suggesting that the regression should also include total revenue and total cost, because profit is calculated as the difference between revenue and cost. However, total revenue and total cost *perfectly* explain profit (which is simply the difference between the two, ignoring taxes); hence, the inclusion of total revenue and total cost renders the regression uninformative about the factors that actually *drive* profit.[53]

II.F. Dr. Erdem's criticism regarding the calculation of standard errors is incorrect and irrelevant

(51) Dr. Erdem implies a criticism of my use of the cable regression coefficients by claiming that Dr. Crawford should have clustered standard errors at the system level rather than at the system-accounting period level, and that this supposed econometric mistake renders the cable coefficients not useful.[54] To be clear, Dr. Erdem's criticism regarding Dr. Crawford's choice of clustering has no effect on the estimated coefficients, which are themselves unaffected by different clustering assumptions, as Dr. Erdem himself points out.[55]

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52 Dr. Crawford made the same point regarding cable allocations in his cable proceeding testimony. *See* Rebuttal Testimony of Gregory S. Crawford, Ph.D. In re Distribution of Cable Royalty Funds, No. 14-CRB-0010-CD (2010-13) (filed March 15, 2017) (hereinafter "Crawford Written Direct Testimony"), ¶ 91. ("To understand the consequences of Dr. Erdem's inclusion of his "distant subscribers" variable requires a brief consideration of the goal of an econometric analysis in this proceeding. In general, econometrics is often used for one of two broad purposes: (a) to predict a particular economic outcome and (b) to understand the effects of particular explanatory variables on a particular outcome. Both are reasonable (but very difficult) goals. For the goal of prediction, the focus is on finding the explanatory variables that best predict the outcome of interest, without regard (necessarily) to what those variables are or what their individual effects on the prediction. In other words, if the goal is to predict stock prices and the price of tea in China helps, then so be it: include it in the model (and don't worry about the economic interpretation of its coefficient).")

53 Dr. Erdem purports to study the effects of alternatives to Dr. Crawford's control for system size, as well as differences in compensability between the cable and satellite context, with six additional sensitivity models discussed at Erdem Amended Satellite WDT, ¶¶ 122–25, 129–33. This is the discussion of his "Question #3." As with his other sensitivity models, I disagree with his interpretation of these permutations as tests of the Crawford regression.

54 *See* Erdem Amended Satellite WDT, ¶¶ 89, 94, 106.

55 *See* Erdem Amended Satellite WDT, ¶ 126. ("Models 12–23 are estimated similarly to Models 0–11, except rather than clustering standard errors at the system and accounting period level as Dr. Crawford does, I cluster standard errors only at the system level (allowing for correlations across accounting periods for the same systems). These models are designed to address Question #4 above, and they results in larger standard errors, as Dr. Crawford's implicit assumption that observations for a given system are independent across accounting period is no longer imposed. The coefficient estimates for all claimant categories remain exactly the same.")

(52) Dr. Erdem justifies his assertion based on his assessment that minutes in each claimant category that are retransmitted by a system are likely to be correlated over time.[56] When Dr. Erdem reestimates Dr. Crawford's regression using the alternate level of clustering, the standard errors on the claimant minutes coefficients increase.[57]

(53) Dr. Erdem incorrectly states the rationale behind clustering standard errors. He writes:

> In calculating statistical significance of coefficients, I noticed that Dr. Crawford clustered errors at the system-accounting period level, which effectively assumes that the number of category minutes retransmitted by a system is independent from one accounting period to another (i.e., that system's determination of what to retransmit in each accounting period is completely independent of its determination of what to retransmit in the accounting period before). This implicit assumption struck me as absurd, as a cursory review of the data shows that a system's retransmissions tend to be highly consistent from one accounting period to another, and witnesses have testified that systems prefer not to drop retransmissions of stations carried.[58]

(54) However, as a technical matter, Dr. Erdem's assertion is flawed. Dr. Erdem's criticism misstates the assumptions and rationale of clustering standard errors in a regression model. He asserts that Dr. Crawford's specification implicitly assumes that *the number of category minutes* retransmitted by *a system* is independent from one accounting period to another. This is incorrect. Dr. Crawford's specification does not rely upon any assumption about the independence of *the number of category minutes*. What Dr. Crawford's specification implicitly assumes is that the log of a subscriber group's royalty is independent, after controlling for all other variables in the regression as well as the system-accounting-period (i.e., system-time) fixed effect.[59] The intertemporal correlation of system-level programming practices that Dr. Erdem is concerned about is absorbed by the system-accounting period fixed effects and hence does not result in correlation in the regression residuals. This is another advantage of Dr. Crawford's fixed effects specification.

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[56] *See* Erdem Amended Satellite WDT, ¶¶ 89, 106 (at ¶ 106: "As I stated in Paragraph 89 above, Dr. Crawford's use of system–accounting period standard errors effectively assumes that the number of category minutes retransmitted by a system is independent from one accounting period to another. This assumption struck me as absurd, because a system's retransmissions tend to be highly consistent from one accounting period to another.")

[57] *See* Erdem Amended Satellite WDT, ¶ 89.

[58] *See* Erdem Amended Satellite WDT, ¶¶ 89.

[59] A. Colin Cameron and Pravin K. Trivedi, *Microeconometrics: Methods and Applications* (New York: Cambridge University Press, 2005), 830–31; Joshua D. Angrist and Jörn–Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton, NJ: Princeton University Press, 2009), 309–12. Clustered standard errors provide an alternative measure of precision of regression coefficients when data are sampled in clusters, i.e., when the independent variables (regressors) vary by cluster even though the dependent variable exhibits variation within cluster. In such cases, the standard error will not capture the true variability in the data and a "clustered standard error" is one modification of the typical standard error that econometricians use to adjust for this problem.

(55) Although Dr. Erdem's original justification is flawed, I agree that it is at least plausible that under certain conditions, clustering the standard errors at the system level could make sense. For example, system-level clustered standard errors could be useful to address concerns that log royalties are correlated over time within a system even after controlling for the system-accounting-period fixed effect and other variables in the regression. If Dr. Erdem's hypothesis is correct, and residuals are correlated in this way, then one response might be to calculate the clustered standard errors at the system level.

(56) All this said, however, Dr. Erdem's critique is ultimately irrelevant. When Dr. Erdem clusters the standard errors at the system level (in his Model 12), the minutes of all claimant categories except devotional remain highly statistically significant,[60] and the coefficient on devotional minutes remains more than marginally statistically significant.[61] As noted previously, the coefficients themselves are unaffected by alternative standard error clustering assumptions. Thus, even under Dr. Erdem's assumption regarding the structure of residuals, all the coefficients of interest are sufficiently statistically significant, in my opinion, to give one confidence in using those for allocation purposes.[62]

(57) Moreover, although all the estimated standard errors increase under Dr. Erdem's alternative assumption, the main reason that the measured statistical confidence drops below the (arbitrary) 1% confidence interval for the coefficient on devotional minutes is simply that the coefficient measuring the value of the devotional minutes is already relatively small, not that the standard error of that coefficient estimate is particularly large relative to the others.

(58) This discussion of statistical significance points out another important error that Dr. Erdem makes in his testimony. Throughout his evaluation of various cable modeling permutations, as presented in section IX of his testimony,[63] Dr. Erdem chooses to replace coefficients that are negative or are not sufficiently "statistically significant" with zero, and then to calculate resulting shares.[64] The treatment

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60 I define highly significant as having less than 1% probability of a coefficient this high occurring by chance if the true coefficient is zero.

61 The coefficient of devotional minutes has a p–value of 6.8%—that is, the probability of a coefficient this high by chance, if the true coefficient is zero, is only 6.8%. I consider a coefficient to be marginally significant if the p–value is less than 10%.

62 Dr. Erdem examines an alternative assumption regarding the estimation of standard errors on the coefficients by implementing clustered standard errors at the system level for all the other sensitive models that he studies. He discusses these results to evaluate the standard error assumptions that he refers to as his Question #4, at Erdem Amended Satellite WDT, ¶¶ 126–32. With the exception of Model 12, the model that implements Dr. Crawford's regression with an alternate standard error assumption, all the rest of these models suffer from the same deficiencies that invalided their purported purpose in the original version with system-accounting period-clustered standard errors. Dr. Erdem's Model 12 is the only sensitivity from which useful insights can be gained, as it is a valid test of the effects of an alternative assumption, namely to cluster at the system level. Dr. Erdem misinterprets the results of Model 12 as well, however. Correctly interpreted, that model shows that it makes no practical difference which of the two standard error estimation assumptions is used.

63 *See* Erdem Amended Satellite WDT, ¶¶ 95–132.

64 *See* Erdem Amended Satellite WDT, ¶ 108. ("After calculating the coefficients in each claimant category using my recreated cable regression data based on Dr. Crawford's code, I calculate the implied shares for each claimant category using the satellite data on minutes of programming by claimant category using the satellite data on minutes of

of negative coefficients in a context where the economic interpretation of the variable implies a value that is non-negative is difficult, and setting such a coefficient to zero is not unreasonable. However, Dr. Erdem's choice to reset a coefficient to zero only because its measured significance falls below an arbitrarily chosen cut-off is unreasonable. I am not aware of any support for this procedure in the economic literature. In fact, quite the contrary. It is inappropriate to impose arbitrary cut-offs motivated merely by fixation with round numbers like 1%, 5%, or 10%. Arbitrary cut-offs around round number measures of statistical significance are particularly problematic when used to look at model permutations and perturbations, as these may cause relatively minor changes in measured significance that cross such a threshold.[65]

(59) Dr. Erdem's error in misinterpreting the statistical significance of his so-called sensitivity tests is compounded by his decision to arbitrarily replace the estimated coefficient (which regardless of its measured statistical significance typically remains the best available estimate of the true coefficient in the context of that OLS model specification) with zero, and then uses the fact of that illogical result to draw further unsupported inferences about the "unreliability" of some other model that has not employed this practice.[66]

programming by claimant category and share calculation code provided by Dr. Heeb. The claimant categories with negative coefficients or coefficients that are not statistically significant are set to zero, and shares are calculated for all other categories.")

65 Andrew Gelman and Hal Stern, "The Difference Between 'Significant' and 'Insignificant' Is Not Itself Statistically Significant," *American Statistician*, 60, no. 4 (2006): 328–31.

66 In his section IX., Model sensitivities, Dr. Erdem repeatedly examines results of inappropriate and unsupportable perturbations of Dr. Crawford's cable model, replaces the non-significant and negative coefficients with zero, and then touts the resulting nonsensical shares as somehow indicating that Dr. Crawford's model is "unreliable" (*see* Erdem Amended Satellite WDT, ¶ 117, 118, and 121); "nonsensical" (*see* Erdem Amended Satellite WDT, ¶ 115); "introduces distortion" (*see* Erdem Amended Satellite WDT, ¶ 122); and "flaw[ed]" (*see* Erdem Amended Satellite WDT, ¶ 125). He summarizes these model results in Exhibit 13 (*see* Erdem Amended Satellite WDT, 62) and the resulting shares in Exhibit 14 (*see* Erdem Amended Satellite WDT, 70). I disagree with both his interpretation of these models as valid tests of the Crawford cable regression model and with the conclusions he draws from the results, without exception, for all 23 model permutations that he examines.

III. Rebuttal to Dr. Rubinfeld

(60) Dr. Rubinfeld makes three assertions regarding the regression framework that Dr. Crawford used in the 2010–2013 Distribution of Cable Royalty Funds Proceeding (hereinafter, "cable case"). The first assertion claims that causal interpretation in Dr. Crawford's model is invalid because the specification is neither in the form of a "hedonic" model nor derived from some more formal structural framework.[67] The second assertion goes further, claiming that *any* regression framework that is used to recover relative market values of programming types "will likely reflect a misinterpretation."[68] The third assertion consists of a list of claims, each suggesting that Dr. Crawford's regression cannot be relied upon to determine relative values of programming types.[69] All these assertions are incorrect and stem from mischaracterizations of Dr. Crawford's model and its application to the satellite case. I will address each of Dr. Rubinfeld's assertions in turn, beginning with the first.

III.A. Hedonic regressions are irrelevant to my analysis, and the requirement of a structural model runs counter to leading empirical research

(61) Dr. Rubinfeld criticizes Dr. Crawford's regression for not being in the format of a "true hedonic model."[70] However, the concept of a hedonic regression is not relevant to the analysis that I present in my Testimony. Moreover, neither I nor Dr. Crawford have described Dr. Crawford's regression framework as hedonic.[71] Absent a hedonic framework, Dr. Rubinfeld argues that a structural

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67 *See* Rubinfeld Amended WDT, ¶ 11. ("In an ideal world, with a different pricing mechanism, a Waldfogel-type regression could provide reliable estimates of the effects in the current proceeding. To be specific, an appropriate *hedonic regression model* formulation might explain the price of a service as a function of the characteristics of that service. For the hedonic model to be applied with reliability, however, a number of assumptions must hold. In cable and satellite royalty proceedings, these assumptions are unjustified.") The alternative condition of a structural model is suggested at ¶ 60, where the hedonic model is discussed in more detail.

68 *See* Rubinfeld Amended WDT, ¶ 11. ("The royalty rates are set by regulation and not based on marketplace valuations. As a result, the variation in the dependent variable in a Waldfogel-type regression that measures satellite royalty fees will be due primarily to variation in the number of subscribers, not the royalty rate. Any attempt to infer relative or absolute dollar valuations will likely reflect a misinterpretation.") The term "Waldfogel-type" regression denotes a broader class of regressions which includes Dr. Crawford's regression model.

69 *See* Rubinfeld Amended WDT, ¶ 69–106.

70 *See* Rubinfeld Amended WDT, ¶ 53. ("A hedonic framework requires variation in market prices and product characteristics. As it relates to this matter, there would need to be variation in royalty rates in the marketplace on the basis of product characteristics such as minutes of programming.")

71 The words "hedonic regression" appear nowhere in my Written Direct Testimony, nor does the term appear in any of the Testimony provided by Dr. Crawford. Based on the testimony and transcripts that are publicly available, it would seem that Dr. Rubinfeld is attributing the claim that a Waldfogel regression is a hedonic-type model to a statement in the transcript of Dr. Mark Israel's testimony in the 2010–2013 Cable Proceedings, where Dr. Israel referred to his model as "very similar to something in industrial organization called a hedonic regression." (*See* Allocation Hearing Transcript of Gregory S. Crawford. Volume XIII, Mar. 12, 2018 (hereinafter "Cable Hearing Transcript, day 13"), 3112).

economic model is required in order to interpret Dr. Crawford's regression coefficients.[72] This point of view is at odds with modern empirical research.

(62) Empirical research does not require a structural model for causal inference. It is very common practice to examine non-price effects of some treatment on a dependent variable of interest. For example, in one recent well-known study, Dr. Nicholas Bloom of Stanford University and co-authors examine the impact of management on worker productivity.[73] There is no abstract model in this study. The causal inference is based on the combination of (i) the concept that good management is connected to worker productivity and (ii) a regression that quantifies this connection.

(63) More generally, the economics literature is rife with examples that make direct causal inferences without the aid of prices or an abstract structural model. I list a sample of recent articles from a wide variety of fields of study, including some drawn from among the most respected journals in economics:

- In a renowned 2005 paper, Dr. Douglas Almond of Columbia University and co-authors determine the impact of low newborn birth weight on infant health.[74] In this study the "treatment" group consists of low-birth-weight newborns and the dependent variable is infant health.
- A study by Dr. Amy Finkelstein of the Massachusetts Institute of Technology (MIT) and Dr. Robin McKnight of Wellesley College finds the impact of the introduction of Medicare in 1965 on mortality rates of the elderly.[75] The treatment variable in this paper is the provision of subsidized health insurance and the dependent variable is elderly mortality rate.
- Dr. Chris Herbst of Arizona State University studies the effect of variation in child care subsidies and tax credits on a mother's employment opportunities.[76]

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72 *See* (Rubinfeld Amended WDT, ¶ 60). "I consider that the Waldfogel-type regression that has been relied on by experts in prior proceedings could be intended to be a type of reduced-form econometric model that is derived from some more fundamental consumer-producer theory that has not yet been formalized or articulated in the prior proceedings. However, I am not aware of a structural economic model involving consumer utility maximization, producer profit maximization, potentially bargaining theory, or the like, that has been put forth as the structural model that, when equilibrium conditions are imposed, would ultimately result in a reduced-form specification that is the Waldfogel-type model. *Without that, it is difficult to know which variables ought to be in the regression, which variables ought not to be in the regression, and how one should interpret the coefficients on those variables.*") [Emphasis added]

73 Nicholas Bloom, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen, "What Drives Differences in Management Practices?" *American Economic Review*, 109, no.5, (2019): 1648–83.

74 Douglas Almond, Kenneth Y. Chay, and David S. Lee, "The Costs of Low Birth Weight," *Quarterly Journal of Economics*, 120, no. 3 (2005): 1031–83.

75 Amy Finkelstein and Robin McKnight, "What Did Medicare Do? The Initial Impact of Medicare on Mortality and Out of Pocket Medical Spending," *Journal of Public Economics*, 92, no. 7 (2008): 1644–68.

76 Chris M. Herbst, "The Labor Supply Effects of Child Care Costs and Wages in the Presence of Subsidies and the Earned Income Tax Credit," *Review of Economics of the Household* 8, no. 2 (2010): 199–230.

- Dr. Joshua Angrist of MIT and co-authors examine the effect of charter schooling on education outcomes. The treatment is "years of charter school education" and the dependent variable is "charter school effectiveness" measured by change in test scores.[77]
- In a pair of papers, Dr. Jonathan Gruber of MIT and co-authors examine the impact of subsidized early childhood education on long-term cognitive (e.g., test scores) and non-cognitive (e.g., pro-social behavior) outcomes. In this study, the "treatment" is the subsidy and a range of dependent variables measures cognitive and non-cognitive outcomes.[78]
- Finally, in a recent study Dr. Raj Chetty of Harvard University and co-authors use regression analysis to show that propensity to innovate in later life is shaped by early-age exposure to innovation. In this example, treatment is early-age exposure to environments in which innovation takes place and the dependent variable is propensity to innovate (which the authors measure using patent records).[79]

(64) Two features are common to each of these studies. First, variation in the dependent variable is coming directly from variation in the treatment as opposed to being mediated by price or some alternative market mechanism. Second, all these studies make direct causal inferences and justify these inferences based on the quality of the empirical research design, as opposed to a structural model.

III.B. Dr. Crawford's regression does identify the relative value of claimant minutes

(65) Dr. Rubinfeld goes further than criticizing Dr. Crawford's specification. Dr. Rubinfeld states that any data set that links royalties to content types, such as in the cable and satellite proceedings, cannot be used to "reveal fair market value" of programming types.[80] This blanket assertion misses the point of the current exercise, which is to establish *relative* values of the contributions of different copyright holders to the royalty pool in a manner that reflects what these relative values would be in a

[77] Joshua D., Angrist, Parag A. Pathak, and Christopher R. Walters, "Explaining Charter School Effectiveness." *American Economic Journal: Applied Economics* 5, no.4 (2013): 1–27.

[78] Michael Baker, Jonathan Gruber, and Kevin Milligan, "Universal Child Care, Maternal Labor Supply, and Family Well-Being," *Journal of Political Economy* 116, no. 4 (2008):709–45; Michael Baker, Jonathan Gruber, and Kevin Milligan, "The Long-Run Impacts of a Universal Child Care Program," *American Economic Journal: Economic Policy* 11, no. 3 (2019): 1–26.

[79] Alex Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "Who Becomes an Inventor in America? The Importance of Exposure to Innovation," *Quarterly Journal of Economics* 134, no. 2 (2019): 647–713.

[80] *See* Rubinfeld Amended WDT, ¶ 63. ("I do not rule out the possibility that some regression might be proposed that could potentially provide corroborative or supporting evidence to the results from a more suitable framework for studying the question more directly, such as a valid statistical survey that attempts to ascertain the market value of programming types by directly asking willing buyers (the survey respondents) about their choices and valuations. *But I do not see how any of the regression specifications used in the cable proceeding, including Professor Crawford's Waldfogel-type cable regression that was relied on by Dr. Heeb in the current stage of the proceeding, can reveal fair market value, given the failure of the necessary assumptions that these specifications entail.*") [Emphasis added]

hypothetical marketplace. The Crawford regression, like the other Waldfogel-like regressions used in earlier proceedings, is designed to capture exactly that.

(66) In his testimony in the cable case Dr. Crawford explained the rationale for why his regression model does reveal relative market value.

> [I]f a system decides to include a distant signal in one of its subscriber groups but not another, it likely does so because it thinks the programming contained on that distant signal will increase the number of subscribers among the households in the communities served by that subscriber group. If that indeed happens, the royalty paid in that subscriber group will be higher than in other subscriber groups, identifying the effect of the valuable programming contained in the distant signal.[81]

(67) I agree with Dr. Crawford. The hypothetical marketplace and the actual distant signal carriage choices made by real cable system operators have at least one critical characteristic in common. In both settings, operators are assumed to add programming by selecting incremental distant signal stations (and the corresponding minutes of programming of different claimant groups) until the benefits of additional programming in terms of appealing to their customers and potential customers are balanced against the additional cost to the operators in royalty payments. This implies that variation in programming minutes can be used to identify relative market values, which is precisely what the Crawford regression captures (and which is formally stated in Appendix A.2. of Dr. Crawford's testimony).[82]

(68) The Judges have explicitly recognized both this objective of the royalty allocation exercise, and the explicit interpretation given by Dr. Crawford that is consistent with that objective:

> [T]he *raison d'être* of this section 111 proceeding is to allocate royalties *that have already been paid* in a manner that reflects relevant market factors. To do so, it is

[81] *See* Crawford Corrected Cable Testimony, ¶ 126. ("Variation across subscriber groups within a system at a given point in time and across time within a given subscriber group are both *excellent* sources of variation on which to base a statistical estimation, as they are closely tied to cable system decision-making. In the first case, if a system decides to include a distant signal in one of its subscriber groups but not another, it likely does so because it thinks the programming contained on that distant signal will increase the number of subscribers among the households in the communities served by that subscriber group. If that indeed happens, the royalty paid in that subscriber group will be higher than in other subscriber groups, identifying the effect of the valuable programming contained in the distant signal.")

[82] *See* Crawford Corrected Cable Testimony, ¶ 169. ("The marginal value of a programming minute of type c is the estimated change in the royalty paid by a cable system in response to a one-minute increase in the number of minutes of programming type c. Mathematically, it is given by the derivative of the royalty with respect to the minutes of programming type c, $MV_{c,g,s,t} = \partial Royalty_{g,s,t}/\partial mins_{c,g,s,t}$, where "MV" stands for "Marginal Value." Due to the econometric model's log-linear functional form, $MV_{c,g,s,t}$ is not constant, but depends on the royalty paid in subscriber group g of system s in period t: $MV_{c,g,s,t} = \frac{\partial Royalty_{g,s,t}}{\partial mins_{c,g,s,t}} = \frac{\partial Royalty_{g,s,t}}{\partial \log(Royalty)_{g,s,t}} \times \frac{\partial \log(Royalty)_{g,s,t}}{\partial mins_{c,g,s,t}} = Royalty_{g,s,t} \times \beta_c$. The *estimated* marginal value of a programming minute of type c then follows by using the estimated value for $\beta, \hat{\beta}_c$ in the equation above: $\widehat{MV}_{c,g,s,t} = Royalty_{g,s,t} \times \hat{\beta}_c$.")

> sufficient to relate CSO's revealed preferences among program categories, whether through a CSO survey or a regression analysis, to the sum of royalties paid. Prior determinations may have described the allocations that resulted as *the* "relative market value," but there is no doubt that royalties determined in these ways reveal "relative values" that are based on the critical market factor of identified preferences.[83] (Emphasis is in original)

(69) In fact, the Judges go further and outright reject Dr. Rubinfeld's claim (which mirrors claims made by Dr. Erdem in his testimony) that regression analysis could not be used to reveal relative market values.[84] The Judges point out that prior proceedings have dismissed the point raised by Dr. Erdem (and repeated here by Dr. Rubinfeld) and furthermore the Judges explicitly state that they have seen nothing that warrants a change in position.[85]

(70) Neither I nor Dr. Crawford are estimating, say, characteristics of subscriber demand for which a more complicated framework, e.g., a structural model of the type Dr. Rubinfeld loosely describes (Rubinfeld Written Direct Testimony, ¶ 60), might be relevant. Moreoever, Dr. Rubinfeld's criticisms of Dr. Crawford's regression strategy illustrate the adage that the best is the enemy of the good. In my opinion, Dr. Crawford's regression in the cable context provides a robust, reliable, and empirically sound estimate to inform the satellite royalty allocation. To the extent that they can be put to practical use, Dr. Rubinfeld's criticisms of those cable regressions may be informative in some future proceeding to make still further advances. However, in my opinion, Dr. Rubinfeld's criticisms do not diminish my enthusiasm for or confidence in recommending the application of the cable regression coefficients to inform the satellite allocation.

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83 *See* CRB Final Determination, 9 at ¶ 1. ("Because the pricing of the licenses is regulated, however, it is not possible to identify the actual royalties that would be established by these ranked preferences…Nonetheless, the *raison d'être* of this section 111 proceeding is to allocate royalties *that have already been paid* in a manner that reflects relevant market factors. To do so, it is sufficient to relate CSO's revealed preferences among program categories, whether through a CSO survey or a regression analysis, to the sum of royalties paid. Prior determinations may have described the allocations that resulted as *the* "relative market value," but there is no doubt that royalties determined in these ways reveal "relative values" that are based on the critical market factor of identified preferences.")

84 *See* Dr. Erdem's assertion as described in the CRB Final Determination, 12, ¶ 4: "First, according to Dr. Erdem, CSO royalty payments are uninformative because they are determined by a statutory formula, not through free-market negotiations between CSO's and content owners." *See* Rubinfeld Amended WDT, ¶¶ 62–63, Dr. Rubinfeld's assertion: "Multiplying (these) royalty rate by their respective number of subscribers receiving the distant signal results in the total royalty fee that would be used as the dependent variable in a Waldfogel-type regression. The key question is whether a regression based on such a dependent variable could provide reliable estimates of the marginal value of the programming types that could then be used to determine the relative marketplace value of the programming types. In my view, there is no reason to believe that a regression based on statutory royalty fees will reliably identify the marginal value of programming that would prevail if the royalty fees were instead determined in a free market."

85 *See* CRB Final Determination, 13 at ¶ 1. ("The Judges have found previously that Waldfogel-type regressions are relevant in cable distribution proceedings and find nothing in Dr. Erdem's testimony in the current proceeding to support changing that position. Therefore, the Judges reject Dr. Erdem's broad argument that Waldfogel-type regressions are not useful in establishing relative value in this proceeding.")

III.C. Variation in programming minutes induces meaningful variation in subscriber royalties and provides reliable estimates of the relative values of programming

(71) Dr. Rubinfeld also criticizes specific aspects of Dr. Crawford's model and its application to the satellite setting. In this part of his report, there is no single organizing concept underlying his claims. The aim seems to be to cast doubt on the estimates implied by the model by suggesting that it relies on assumptions that may not hold in the satellite and/or cable context.[86] I show below that these assertions do not have merit, but stem from incorrect characterizations of Dr. Crawford's regression and the manner in which I apply it to the satellite context.

(72) Dr. Rubinfeld asserts that the presence of statutory royalty fees has two consequences: (i) it prevents "meaningful price variation" based on programming minutes, and (ii) it does not "address negative correlation for programming types."[87] The second point misses the objective of Dr. Crawford's econometric exercise. As noted by Dr. Crawford and cited by the Judges, negative correlation of programming types is implicit in his regression analysis since programming decisions by CSOs are driven by revenue maximization, which "identified (*sic*.), ranked, and estimated the relative value of program categories that maximize economic value for subscribers given the existence of retransmission costs."[88] In other words, the notion that subscribers' willingness to pay for programming content is negatively correlated across programming types motivates a CSO's bundling decisions but, beyond providing motivation, is irrelevant to the question of reliability of Dr. Crawford's regression coefficients.

(73) Dr. Rubinfeld's claim that statutory royalty fees prevent "meaningful price variation" mischaracterizes both the objective of Dr. Crawford's regression and the economics underlying it. In

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86 *See* Rubinfeld Amended WDT, pp. 25–42 covering section B ("Reliable Econometric Estimation of the Marginal Value of Programming is Impeded by the Realities of the Marketplace and the Statutory Environment") and section C ("Other Assumptions Required for Reliable Econometric Results Are Not Plausible").

87 *See* Rubinfeld Amended WDT, ¶¶ 69–76. (Following the subsection titled "There is Little Meaningful Price Variation Based on Programming Content," Dr. Rubinfeld states, "The statutory satellite royalty fee per subscriber per month varies on only two dimensions: it increases over time from \$0.25 to \$0.27 for private home viewing subscribers and \$0.50 to \$0.54 for commercial subscribers, and it differs for private home viewing versus commercial subscribers, in which the latter is approximately twice the former. Multiplying these royalty rates by their respective subscriber counts results in the total royalty fees (in dollars) that would be used in a Waldfogel-type regression. However, the lack of variation in per subscriber royalty fees poses a potentially serious misspecification problem that would render such an analysis uninformative. Specifically, the marginal effects estimated in such a regression might tell us something about the number of subscribers receiving the programming, all else equal. But it does not tell us anything about the marginal value of the programming based on dollar royalty fees if royalties were determined in a competitive market.") and at Rubinfeld Amended WDT, ¶¶ 65–68. ("Neither the cable nor the satellite data contains the kind of demographic information (either by geography or nationwide) that would be needed in a regression investigating how "negative correlation" affects value of—or even just demand for—different categories of programming.")

88 *See* CRB Final Determination, 17 at ¶ 6. ("In response to the first point, Professor Crawford noted that his regression analysis implicitly incorporated this revenue maximization principle because it identified, ranked, and estimated the relative value of program categories that maximize economic value for subscribers given the existence of retransmission costs.")

his testimony, Dr. Crawford noted that one of the key factors driving cable operators' bundling choices was "the difference between marginal cost and mean willingness-to-pay" for content.[89] It follows that variations in royalty payments identify relative programming values precisely because system operators' choices, which determine royalty payments, reflect the anticipated value of this programming to its customers. And, as Dr. Crawford has explained, the "most suitable" econometric regression to estimate this relationship relates "distant signal royalty payments to the minutes of programming of different types carried on distant signals under the compulsory license."[90]

(74) It is important to keep in mind that the economic relationship that is being estimated is the one between programming minutes and royalty payments, *not* royalty fees. This may seem like an obvious point, but it seems to be an important part of Dr. Rubinfeld's assertion that variation in fees is what is necessary to determine relative programming values.[91] Dr. Rubinfeld's requirement that inference on relative programming values can only be made using variation in per subscriber fees runs counter to econometric practice, as well as to the estimation method put forth by Dr. Crawford and accepted by the Judges.[92] Certainly variation in per subscriber fees obtained in a marketplace in which such prices vary would be even more useful to determine values (especially absolute values, as opposed to relative values), if such prices were available. However, the menu choices economic actors make among alternatives whose values vary can and do provide information about the relative value of these alternatives. Those values can be inferred from the observed choices made by those actors.[93]

(75) Dr. Rubinfeld makes the assertion that "it is implausible to assume that minutes of programming are a reliable proxy for the value of the programming type" and offers a series of claims that attempt to

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89 *See* Crawford Corrected Cable Testimony, ¶ 23. ("In a study published in *Information Economics and Policy* in 2007, Joseph Cullen and I simulated outcomes in an "average" cable television market to investigate the effects of selling channels in bundles on cable operators and subscribers. We concluded that "two key factors determine the consequences of bundling on [cable operators'] profit…the difference between marginal cost and mean WTP [willingness-to-pay] for [channels] and [negative] correlation in that WTP for [channels].")

90 *See* Crawford Corrected Cable Testimony, ¶ 46. ("I conclude that an econometric analysis relating existing distant signal royalty payments to the minutes of programming of different types carried on distant signals under the compulsory license is most suitable for determining the relative marketplace value of the programs actually retransmitted between 2010 and 2013.")

91 *See* Rubinfeld Amended WDT, ¶ 69. ("Specifically, the marginal effects estimated in such a regression might tell us something about the number of subscribers receiving the programming, all else equal. Multiplying these royalty rates by their respective subscriber counts results in the total royalty fees (in dollars) that would be used in a Waldfogel-type regression. However, the lack of variation in per subscriber royalty fees poses a potentially serious misspecification problem that would render such an analysis uninformative.")

92 *See* CRB Final Determination, 13 at ¶ 1. ("The Judges have found previously that Waldfogel-type regressions are relevant in cable distribution proceedings and find nothing in Dr. Erdem's testimony in the current proceeding to support changing that position. Therefore, the Judges reject Dr. Erdem's broad argument that Waldfogel-type regressions are not useful in establishing relative value in this proceeding.")

93 The studies that I cite in section III.A illustrate the wide range of topics on which economists use choices over unpriced alternatives to infer information about relative value, contributions, or effectiveness of those alternatives. In many cases such studies employ those techniques precisely because there are no direct market measures that capture the relative value of the alternatives.

support this assertion. I will address the series of claims separately, but regarding his main assertion, neither Dr. Crawford nor I have suggested that programming minutes, by themselves, proxy for value of programming type. The correct statement, as stated in Dr. Crawford's report (see Appendix A.2), is that the *regression coefficient* on distant signal minutes of a given programming type *multiplied by* cable operator royalty fees measures marginal value of that programming type.[94] Hence, the statement that I use minutes of programming to "proxy" for value of programming is not correct.

(76) Dr. Rubinfeld claims that variation in distance minutes of programming is "not a reliable measure of marketplace value" using the example of station programming that is widely viewed but would be assigned low marginal value under Dr. Crawford's regression:

> [B]ecause most subgroups receive WGNA on a distant basis, the minutes of programming on WGNA contribute little to the statistical variation in the WGNA data, with the *counterintuitive* result that the minutes on the most widely retransmitted station will have the least influence on the regression coefficients.[95] [Emphasis added]

I disagree with the assertion that this is a "counterintuitive" finding. The critical point is that shares take both incremental values, i.e., the coefficients of the Crawford regression, *and* total minutes, into account. An extra minute of a program that is available everywhere and viewed by everyone might be valued less than an extra minute of programming that is less widely available but maintains a strong niche viewership. At the same time, the fact that the niche program has higher incremental value does not entitle it to a larger share of royalties. What Dr. Rubinfeld's example does is provide a clean and *intuitive* illustration of how the Crawford equation comes to the correct allocation of royalty shares; i.e., a popular program type with low marginal value may obtain much of the royalty, without pushing out niche programming with low viewership but high marginal value.[96]

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94 *See* Crawford CWDT, ¶ 169.

95 *See* Rubinfeld Amended WDT, ¶ 87. ("However, because most subgroups receive WGNA on a distant basis, the minutes of programming on WGNA contribute little to the statistical variation in the WGNA data, with the counterintuitive result that the minutes on the most widely retransmitted station will have the least influence on the regression coefficient. Minutes on a station retransmitted on a distant basis to all subgroups within a system contribute nothing to variation, and therefore to the regression coefficient.")

96 At Rubinfeld Amended WDT, ¶ 97 of his written testimony, Dr. Rubinfeld asserts that devotional programming is largely carried on WGNA (his cited evidence for this is Dr. Erdem's report, Exhibit 4) and claims that this implies the "marginal value of devotional programming as estimated by Professor Crawford's regression coefficient is likely to fall– because most cable subgroups carry WGNA with its substantial devotional programming." The same claim (i.e., that broadly retransmitted signals will induce a biased estimate for value of programming carried on those signals) is made in ¶ 97. The fact that WGNA is carried on many systems would potentially affect only the sharpness of the regression estimate, but by itself it says nothing about the potential bias of the estimate, i.e., whether Dr. Crawford's regression over or underestimates marginal value of a given programming type. Moreover, Dr. Crawford's estimates (Crawford Written Direct Testimony, Figure 16, p. 40) are statistically significant for all claimant groups. Hence, in the actual data, there is enough variation to obtain precise estimates.

(77) Dr. Rubinfeld makes a further claim that in the cable proceeding, broad retransmission results would be expected to "bias the coefficients downward for program types that have more minutes on those stations […] because there is a reduction in variability in program minutes from subscriber group to subscriber group."[97] While it is true that broad retransmission may result in less precise estimates, this concern is an empirical one. In fact, the results of Dr. Crawford's cable regression are statistically significant for the variable of interest.[98] There is sufficient variability in these data, including variability in the devotional minutes, to estimate the coefficients with sufficient precision to reasonably and reliably allocate the collected royalties. Other significant assumptions would have to be made and justified to support the conclusion that broad retransmission itself generates any bias, and to establish the direction of such bias.

(78) Dr. Rubinfeld's claim of bias in satellite regression coefficients is entirely off-point.[99] Neither am I nor is Dr. Erdem proposing to calculate the satellite allocation using satellite regressions. As I observed in my direct testimony, it is infeasible to implement Dr. Crawford's regression estimation approach in the satellite context because the data do not allow for disaggregation at the subscriber-group level, which is the essential identifying characteristic of the Crawford regression.[100] While it may be true that Dr. Erdem's satellite regressions are biased, my understanding of his reason for attempting a satellite regression at all was simply to demonstrate by example the futility of that exercise.

(79) Dr. Rubinfeld makes several additional claims that mirror claims made by Dr. Erdem; my response to these claims is in Section II.[101]

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97 *See* Rubinfeld Amended WDT, ¶ 97. ("In the context of the 2010–2013 Cable Proceeding, the broad retransmission of certain stations (such as WGNA, as a clear example) would be expected to bias the coefficients downwards for program types that have more minutes on those stations.")

98 *See* Crawford Corrected Cable Testimony, Figure 18, 44., where Dr. Crawford reports coefficient estimates and standard errors from his regression.

99 *See* Rubinfeld Amended WDT, ¶ 97. ("This bias occurs because there is a reduction in the variability in programming minutes from subscriber group to subscriber group in those programming types. In satellite, the effect is opposite. The broad satellite retransmission of certain stations (like WGNA) is expected to bias the coefficients upward for program types that have more programming minutes on those stations. In the satellite case, the variability is station to station, rather than from subscriber group to subscriber group.")`

100 *See* Heeb CWDT, ¶ 10. ("In the satellite context, data limitations prevent direct application of Dr. Crawford's methodology. Obtaining satellite-specific regression coefficients on minutes directly from satellite data is infeasible for at least two reasons. First, unlike the cable context, in which multisystem cable operators report distant signal royalties by subscriber group, satellite carriers provide distant signal royalty data by station on a national level. Thus, whereas the cable royalty data are provided at a granularity sufficient to enable a regression controlling for subscriber group characteristics of customers who have access to program lineups, it is not possible to obtain similar data in the satellite context. Second, in the cable context, geographic covariates can be constructed to control for both demographic differences and for varying program options across groups of customers. The satellite data do not provide any information about the geographic locations of the subscribers, thus precluding the ability to analyze the data across these dimensions.")

101 At Rubinfeld Amended WDT, ¶¶ 89–90, Dr. Rubinfeld suggests that compensability of network minutes could alter Dr. Crawford's share estimates. This point mirrors Dr. Erdem's question 2 (*see* section II.D). At ¶¶ 91–94, Dr. Rubinfeld essentially repeats claims raised in Dr. Erdem's question 1 (*see* section II.C). At ¶¶ 104–106, Dr. Rubinfeld raises the same question as Dr. Erdem's Question 4 (*see* section II.F).

Appendix A. Curriculum vitae of Randal D. Heeb, PhD

A.1. Summary of experience

Randal Heeb has 30 years of experience providing economic analysis in both the private and public sectors. His expertise includes analysis of liability, damages, and other remedies in antitrust and intellectual property disputes. Dr. Heeb has written, consulted, and testified on a range of issues related to the application of economic and econometric analyses in a variety of industries, including software, computer hardware, telecommunications, commodities and financial markets, pharmaceuticals, electricity, natural gas, and gaming.

In 2013, Dr. Heeb was recognized by *The International Who's Who of Competition Economists* as one of the world's leading competition economists. He has previously held various academic posts in the United States and Europe and was most recently a Senior Faculty Fellow at the Yale School of Management. He has served private sector clients and public authorities operating in both regulated and unregulated markets, and he has taught antitrust compliance to executives in North America, Europe, and Asia.

A.2. Selected experience

- Submitted an expert report on patent misuse issues in *ChromaDex v. Elysium Health.*
- Submitted an expert report on damages in *In re Packaged Seafood Products Antitrust Litigation*, related to allegations of price fixing in the market for canned tuna.
- Testified before a jury on reasonable royalty damages on behalf of Amgen in a biopharmaceutical patent dispute.
- Submitted written direct testimony before the Copyright Royalty Board *In re Distribution of Satellite Royalty Funds.*
- Testified for NOVA Chemical Company before the Federal Court of Canada on reasonable royalties and patent damages issues.
- In *In re Western States Wholesale Natural Gas Antitrust Litigation*, submitted multiple expert reports and declarations on behalf of energy trading companies alleged to have violated Section I of the Sherman Act, on issues related to class certification, liability and damages.
- Submitted an expert report on reasonable royalties in *Seedlings v. Pfizer* before the Federal Court of Canada.

- Submitted an expert report on damages in *MCQ v. Idaho Pizza Company*, a dispute involving intellectual property licensing in the franchise restaurant business.
- Testified to an arbitration panel on behalf of Activist in *Activist v. Phoenix*, a trade secrets dispute in the residential mortgage-backed securities industry.
- Provided expert testimony on behalf of Tata Consultancy Services Limited on damages issues in a contract dispute over the implementation of an SAP Enterprise Resource Planning system for a global law firm.
- Testified to an arbitration panel in an intellectual property and trade secrets dispute on behalf of Scentsy, Inc.
- In *In re Natural Gas Commodity Litigation*, submitted expert testimony on behalf of Coral Energy Resources, an energy trading company, related to allegations of collusion and price manipulation in the NYMEX commodity futures market.
- Provided economic expert services to the complainants in a steel industry trade dispute before the US International Trade Commission.
- Submitted an expert report on behalf of Central Valle Hermoso, S.A. de C.V., in an international arbitration under the rules of the ICC, in a dispute involving a natural gas supply agreement.
- In *Certain Electronic Devices, Including Wireless Communication Devices, Tablet Computers, Media Players and Televisions, and Components Thereof and Certain Wireless Devices with 3G and/or 4G Capabilities and Components Thereof*, two related ITC investigations involving standard-essential patents (SEPs), served as lead consulting economist.
- Testified before Judge Glazer at the Federal Energy Regulatory Commission on behalf of Shell Energy North America on issues related to allegations of natural gas price misreporting.
- Submitted expert reports and testified before the court in *United States v. Dicristina* regarding econometric and game theoretical evidence on the question of whether poker is a game predominated by skill or chance. Judge Weinstein cited the testimony extensively in his decision.
- Submitted an affidavit in *Cohen v. Minister of Citizenship and Immigration* regarding econometric and game theoretical evidence on the question of whether poker is predominately a game of skill or chance. Judge Harrington cited the affidavit favorably in his decision.
- Submitted expert testimony on damages on behalf of the defendant in a dispute over alleged natural gas and financial derivatives price manipulation in *E. & J. Gallo Winery v. EnCana Corporation*.
- Testimony in a bench trial on the question of whether poker is a game of skill or chance in *Minnesota v. Jerde*, No. 60-CR-12-1715, was cited favorably by Judge Remick in his decision.

- Retained to testify before an arbitration panel on damages for an international seed company, the plaintiff in a patent dispute over licensing of genetic traits for herbicide tolerance. The matter settled prior to testimony.
- Developed damages estimates for mediation in an antitrust and intellectual property dispute in the heavy equipment industry involving issues of bundled pricing and exclusive dealing.
- Lead consulting expert to an international seed company advising on damages and settlement strategy in a defense matter involving licensing of genetic traits for herbicide tolerance before a US District Court.
- Served as lead consulting expert for SAP, defending a patent infringement suit in *Sky Technologies LLC v. SAP AG*.
- Served as lead economics consulting expert on behalf of AMD in the landmark microprocessor antitrust case *AMD v. Intel*. Led the consulting teams supporting three testifying experts and supervised all economics-related contributions. Advised on overall case strategy and performed economic analysis to assess liability and damages resulting from alleged illegal conduct in the United States, Japan, Korea, and Europe.
- Served as lead consulting economist in a matter alleging trade secret misappropriation and antitrust counterclaims of tying, exclusive dealing, and attempted monopolization in the property management software market.
- Led the external economic team supporting the Competition Bureau of Canada's evaluation of the merger of Maple Acquisition Group and the parent company of the Toronto Stock Exchange.
- Retained to submit an expert report on damages for a defendant computer manufacturer in an intellectual property dispute involving component patents. The matter settled prior to testimony.
- Served as lead consulting expert for Amgen, Inc., on issues related to a request for permanent injunction in the patent infringement suit *Teva v. Amgen*.
- Served as lead economics consulting expert on behalf of several plaintiff companies in the Butadiene Rubber (BR)/Emulsion Styrene Butadiene Rubber (ESBR) case, which was argued before the English High Court.
- Provided economic analysis to the Competition Bureau of Canada in its evaluation of the acquisition of Maple Leaf Sports Entertainment by Bell Canada Enterprises Inc. and Rogers Communications, Inc.
- Led the economics team providing advice to the Competition Bureau of Canada in its evaluation of the acquisition of Potash Corporation by BHP Billiton.
- Provided economic analysis on behalf of tire manufacturers in UK proceedings regarding private damages claims related to the European Union synthetic rubber cartel case. Supported testifying expert and worked with attorneys on both sides of the Atlantic to quantify potential damages.

- Led a joint US–European consulting team providing support to a leading firm in the freight forwarding industry to address inquiries from antitrust authorities in a number of jurisdictions throughout the world, including the European Commission and the US Department of Justice, related to allegations of price-fixing and other anticompetitive conduct.
- Led the economics team supporting an expert testifying on behalf of Music Choice before the Copyright Royalty Board of the US Library of Congress.
- Estimated damages related to allegations of natural gas price manipulation and provided advice as a consulting expert.
- Served as Scientist-in-Charge (principal investigator) of a European Union–funded research study of the economics of network industries.
- Provided economic analysis to New England Power Service Company, supporting both the planning and the divestiture of the Seabrook nuclear power station.
- Developed electric utility resource planning and asset valuation methodology and software that was implemented in six states and used by federal government researchers.
- Developed a simulation model to calibrate electricity forecasting and planning methodologies to variations in weather.
- Provided advice to multiple defendants as a consulting expert in support of successful settlement negotiations in a number of state indirect purchaser cases in matters involving allegations of physical natural gas price manipulation.
- Retained as an expert by an energy trading company in a case involving allegations of securities market manipulation in the propane industry.
- Designed and implemented short-term econometric forecasting methodology that is widely used to support trading in deregulated electricity markets.

A.3. Testifying experience

- *ChromaDex, Inc., v. Elysium Health, Inc.*, Case No. SACV 16-02277-CJC(DFMx), (C.D. California). Expert report July 26, 2019, deposition August 14, 2019.
- *In re Packaged Seafood Products Antitrust Litigation*, Case No. 15-MD-2670-JLS-MDD (S.D. California). Expert report, May 10, 2019; deposition, June 7, 2019.
- *Seedlings Life Science Ventures LLC v. Pfizer Canada Inc*., No. T-608-17 (Canada Federal Court). Expert report, May 29, 2019.
- *In re Distribution of Satellite Royalty Funds*, No. 14-CRB-0011-SD (2010-13). Written direct testimony, Mar. 22, 2019, corrected written direct testimony, June 6, 2019.

- *Central Valle de Hermoso, S.A. de C.V. v BNP Paribas*, International arbitration under rules of the ICC. Expert report, February 8, 2018.
- *Amgen Inc. v. Hospira Inc*., Case No. 15-cv-839-RGA (D. Delaware). Expert report, February 3, 2017; reply report, April 13, 2017; deposition, April 28, 2017; jury testimony, September 19, 2017.
- *Los Angeles Turf Club, et al. v. Horse Racing Labs, LLC, et al.*, Case No. 2:15-cv-9332 (C.D. Cal). Expert report, March 8, 2017, corrected expert report, March 15, 2017; declaration April 20, 2017; deposition May 10, 2017.
- *The Dow Chemical Company v. NOVA Chemicals Corporation*, No. T-2051-10 (Canada Federal Court, 2011). Expert report, September 26, 2016; reply report, November 30, 2016; testimony, December 15–16, 2016, January 11, 2017.
- *In re Western States Wholesale Natural Gas Antitrust Litigation*, MDL-1566, Base Case No. CV-S-2:03-1431-RCJ-PAL, Case Nos. CV-S-03-1431-RCJ-PAL, CV-S-06-233-RCJ-PAL, CV-S-07-987-RCJ-PAL, CV-S-07-1019-RCJ-PAL, CV-S-09-00915-RCJ-PAL (D. Nevada). Declaration, June 23, 2016; deposition, August 1, 2016; expert report, September 12, 2016; rebuttal declaration, November 3, 2016; deposition, March 21, 2017.
- *Sinclair Oil Corporation v. ONEOK Energy Services Company, L.P*., MDL-1566, Base Case No. CV-S-2:03-1431-RCJ-PAL. Case No. 2:06-CV-0282-RCJ-PAL. (D. Nevada). Expert report, September 12, 2016.
- *Baker and McKenzie Global Services LLC v. Tata America International Corp*. (AAA Case No. 01-14-0000-0618). Expert report, January 15, 2016; deposition, February 19, 2016; testimony, April 27, 2016.
- *Public Utils. Comm'n of the State of Cal. v. Sellers of Long-Term Contracts to the Cal. Dep't of Water Res*. and *California Elec. Oversight Board v. Sellers of Energy & Capacity Under Long-Term Contracts with the Cal. Dep't of Water Res*., Nos. EL02-60-007 and EL02-62-006 (FERC). Answering testimony, July 21, 2015; deposition, September 22, 2015; cross-examination testimony, November 24, 2015.
- *Activist Special Advisory Services LLC v. Phoenix Real Estate Solutions Ltd*. (AAA Case No. 011400002627). Expert report, February 19, 2015; testimony before arbitration panel, February 25, 2015.
- *Marosvari v. Scentsy, Inc*., No. CV OC 1210673 (Arbitration ordered by Idaho Dist. Ct., Ada Cnty). Expert report, November 17, 2014; deposition, December 5, 2014; testimony before arbitration panel, December 17, 2014.
- *Minnesota v. Jerde*, No. 60-CR-12-1715 (Minn. Dist. Ct., Polk Cnty. filed 2012). Declaration, October 17, 2014; oral testimony in bench trial, November 6, 2014.

- *Minnesota v. Johnson*, No. 60-CR-12-1713 (Minn. Dist. Ct., Polk Cnty. filed 2012). Declaration, October 17, 2014.
- *Cohen v. Minister of Citizenship and Immigration*, No. IMM-7846-14 (Can. Fed. Ct.). Affidavit, December 11, 2013.
- *Kentucky v. Pocket Kings*, No. 10-CI-0505 (Ky. Cir. Ct., Franklin Cnty. Mar. 25, 2010). Affidavit, September 24, 2012.
- *United States v. Dicristina*, No. 11-CR-414 (E.D.N.Y. June 1, 2011). Expert report, July 5, 2012; oral testimony in bench trial, July 9, 2012, August 10, 2012; supplemental expert report, August 13, 2012; declaration, August 20, 2012.
- *MCQ v. Idaho Pizza Co., Inc.*, No. CV OC 1025077 (D. Idaho, Dec. 22, 2010). Expert report, July 11, 2011.
- *E. & J. Gallo Winery v. EnCana Corp*., No. CV F 03-5412 (E.D. Cal. Sept. 30, 2005). Expert report, April 1, 2009; deposition, April 2009.
- *In re Natural Gas Commodity Litig*., No. 03 CV 6186 (S.D.N.Y. Oct. 14, 2004). Expert report, December 5, 2006.

A.4. Professional experience

- Partner, Bates White Economics Consulting, Washington, DC, 2005–present
- Senior Faculty Fellow, Yale School of Management, New Haven, CT, 2009–2011
- Visiting Professor, European School of Management and Technology, Berlin, 2008–2018
- Assistant Professor of Economics, INSEAD, Fontainebleau, France, 1999–2004
- Visiting Assistant Professor of Economics and Strategy, University of Chicago, IL, 2002–2003
- President, Policy Planning Associates, Inc., Seattle, WA, 1986–1999
- Supply Planning Analyst, New England Power Service Co., Westboro, MA, 1984–1986

A.5. Education

- PhD, Economics, University of Chicago
- MPA, Harvard Kennedy School
- BA, Economics, University of Washington

A.6. Publications and working papers

- "A Framework for the Economic Analysis of Exclusionary Conduct" (with B. Douglas Bernheim). In *Oxford Handbook of International Antitrust Economics*. Vol. II, edited by Roger D. Blair and D. Daniel Sokol, 2015.
- "Cartels as Two-Stage Mechanisms: Implications for the Analysis of Dominant-Firm Conduct" (with Leslie M. Marx, William E. Kovacic, and Robert C. Marshall). *Chicago Journal of International Law* 10, no. 1 (2009): 213–31.
- "Innovation and Vertical Integration in Complementary Markets" *Journal of Economics and Management Strategy* 12, no. 3, (2003): 387–417.
- "The Hidden Gender Restriction: The Need for Proper Gender Controls When Testing for Racial Discrimination" (with Alexander Cavallo and Hazem El-Abbadi). In *Intelligence, Genes, & Success*, edited by Bernie Devlin, Stephen E. Fienberg, Daniel P. Resnick, and Kathryn Roeder, 193–214. New York: Springer-Verlag, 1997.
- "Effects of State Regulation on Childcare Prices and Choices" (with Rebecca Kilburn). RAND working paper, 2004.
- "Catching up in Quality." INSEAD working paper, 2002.
- "Optimal Differentiation." INSEAD working paper, 2002.

A.7. Speaking engagements

- Federal Trade Commission-US Department of Justice Workshop. "Conditional Pricing Practices: Economic Analysis and Legal Policy Implications." June 2014, Washington, DC.
- American Conference Institute. "Paragraph IV Disputes: Expert Insights on Hatch-Waxman Litigation Strategies for Brand Names and Generics." May 2011, New York, NY.
- New York State Bar Association, Antitrust Section. "Counseling clients on exclusionary conduct." March 2011, New York, NY.
- Stanford Institute for Economic Policy Research. "Antitrust and IP Forum." April 2010, Palo Alto, CA.
- European School of Management and Technology. "Cartel Enforcement for Energy Industry Executives." November 2008, Berlin, Germany.
- Econometrics Society Summer Meeting. "Optimal Differentiation." June 2002, Los Angeles, CA.
- École Nationale des Ponts et Chatussées. "Antitrust Issues: The Microsoft Case." April 2002, Paris, France.

- TMR Network Industries Conference. “Optimal Differentiation.” October 2001, Lisbon, Portugal.
- Risk Assessment Conference, INSEAD. “Nash Bargaining Oligopoly Equilibria.” April 2001, Singapore.
- Faculty of Economics, Universidade Nova de Lisboa. “Catching up in Quality.” March 2001, Lisbon, Portugal.
- Berlin Social Science Research Center (WBZ). “Vertical (Dis)-integration in Complementary Markets.” October 2000, Berlin, Germany.
- TMR Network Industries Conference. “Vertical (Dis)-integration in Complementary Markets.” October 2000, Heidelberg, Germany.
- Society for Economics Design. “Vertical (Dis)-integration in Complementary Markets.” June 2000, Istanbul, Turkey.

A.8. Scholarly journal referee

- *American Journal of Sociology, European Economics Review, International Journal of Industrial Organization, Journal of Economics and Management Strategy, Journal of Industrial Economics, Journal of Policy Analysis and Management, Journal of Political Economy, Journal of the European Economics Association, RAND Journal of Economics*

DECLARATION OF RANDAL D. HEEB

I declare under penalty of perjury that the foregoing is true and correct.

Executed on: August 26, 2019

Randal D. Heeb

Randal D. Heeb

Proof of Delivery

I hereby certify that on Monday, August 26, 2019, I provided a true and correct copy of the Allocation Phase Rebuttal Case of the Commercial Television Claimants to the following:

Spanish Language Producers, represented by Brian D Boydston, served via Electronic Service at brianb@ix.netcom.com

Devotional Claimants, represented by Clifford M Harrington, served via Electronic Service at clifford.harrington@pillsburylaw.com

American Society of Composers, Authors and Publishers (ASCAP) and Broadcast Music, Inc. (BMI), represented by Joseph DiMona, served via Electronic Service at jdimona@bmi.com

Settling Devotional Claimants, represented by Jessica T Nyman, served via Electronic Service at jessica.nyman@pillsburylaw.com

SESAC, Inc., represented by John C. Beiter, served via Electronic Service at jbeiter@lsglegal.com

MPAA-represented Program Suppliers, represented by Gregory O Olaniran, served via Electronic Service at goo@msk.com

Broadcast Music, Inc. (BMI), represented by Jennifer T. Criss, served via Electronic Service at jennifer.criss@dbr.com

Joint Sports Claimants, represented by Michael E Kientzle, served via Electronic Service at michael.kientzle@apks.com

National Public Radio, Inc. (NPR) (submitted comment), represented by Gregory A Lewis, served via Electronic Service at glewis@npr.org

Multigroup Claimants, represented by Brian D Boydston, served via Electronic Service at brianb@ix.netcom.com

Motion Picture Association of America (MPAA)-Represented Program Suppliers, represented by Alesha M. Dominique, served via Email

American Society of Composers, Authors and Publishers (ASCAP), represented by Sam Mosenkis, served via Electronic Service at smosenkis@yahoo.com

Major League Soccer, LLC, represented by Edward S. Hammerman, served via Electronic Service at ted@copyrightroyalties.com

Signed: /s/ Ann Mace